TECHNOLOGY DEVELOPMENT AND DIFFUSION AND INCENTIVES TO ABATE GREENHOUSE GAS EMISSIONS

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Abstract

More technology implies higher welfare. Therefore, it is individually rational to cooperate on technological development. It is not individually rational cooperate on greenhouse gas emission reduction. If technology cooperation only comes with cooperation on emission reduction, incentives to free ride on the emission reduction agreement are reduced. However, countries would prefer to cooperate on technology but not on emission reduction. If technology progresses through a learning-by-doing mechanism, more emission reduction technology does not necessarily imply higher emission reduction. However, for reasonable parameter choices, it does. This implies that technological cooperation is an effective instrument in emission reduction policy, also if that policy is of a non-cooperative nature. It also implies that it is in the best interest of technology leaders to subsidise the export of greenhouse gas reducing technology.

Key words

Climate change, greenhouse gas emission reduction, endogenous technological change, learning-by-doing, optimal emission control, coalition formation

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# 1.	Introduction

Climate change is a long-term problem with strong international externalities. It thus makes sense to look at it from a game-theoretic perspective, and to place technology in the heart of the analysis. This paper investigates the interactions between incentives to cooperate on greenhouse gas emission reduction and endogenous technological development and diffusion.

International cooperation is needed for substantial greenhouse gas emission reduction (Nordhaus and Yang, 1996; Tol, 1999a). However, cooperation on a large scale is not individually rational. The grand coalition is not stable, nor is any coalition with a substantial number of members (Barrett, 1994; Carraro and Siniscalco, 1992, 1993). Game theory suggests two ways to establish cooperation in such a situation. Firstly, one could use transfers, that is, use the social gains of cooperation to compensate the individual losers of cooperation. If utility is transferable, it is known that there is a transfer scheme so that the *potential* Pareto improvement of a cooperative solution can be made into an *actual* Pareto improvement that leaves no one worse off and some better (Friedman, 1991; Gibbons, 1992). However, climate change is such a large problem and differences between countries are so great that the side payments would be very large and unprecedented. Furthermore, money can be transferred but utility cannot. Incomes are so disparate across the world that utility cannot be assumed to be proportional to income. The theoretical prerequisites for compensation thus do not hold, and one can show that in practice there is indeed no Pareto improving transfer scheme possible (Tol, 1997; see also Germain *et al.*, 1998).

Secondly, one can use issue linkage to establish cooperation. Combining problems with different asymmetries in their externalities, one can construct situations in which the incentives to free-ride are substantially if not fully reduced (Cesar and de Zeeuw, 1994). In practice, it is hard to find issues that could be linked to greenhouse gas emission reduction. A number of potential candidates have asymmetries similar to climate change, and thus would increase rather than reduce free-riding incentives. Separate international treaties regulated many potential candidates, so that issue linkage would be impractical from a diplomatic and bureaucratic perspective. Technology diffusion is an issue that is often thought to be a promising candidate for linking to emission abatement (Carraro *et al.*, 1993; Carraro and Siniscalco, 1996; Katsoulacas, 1996). This paper investigates this hypothesis. Because treaties on international trade, investment and intellectual property rights already regulate technology diffusion, the analysis here is restricted to emission reduction technology. Existing emission reduction technology also falls under international regulation, but one can argue that emission abatement technology developed under pressure of the UNFCCC should be regulated under that treaty. Thus, the paper is restricted to the diffusion of new emission reduction technology.

The bulk of the paper adopts learning by doing as the main mechanism by which new technologies emerge; Tol *et al*. (2000) show that our findings on coalition formation also hold for research and development driven technological progress; our findings on incentives for emission reduction readily carry over to R&D. Greenhouse gas emission reduction policy is a matter for national governments. Emission reduction technology development is a matter of commercialising existing and proven technologies, not a matter of fundamental research. Arguably, governments have a role in fundamental research, but should leave applied research to the market (Gomulka, 1990). Thus, governments should not themselves invest in research and development of emission reduction technologies, but provide incentives to firms to do so. In this

paper, the government does so by levying emission taxes. Firms then develop new technology to reduce their emission taxes. To the government, it appears as if the new technology emerges spontaneously, in reaction to past policy. Learning by doing is the appropriate formulation for this phenomenon.

Section 2 looks at the effect of learning by doing on optimal emission reduction trajectories. This section brings nothing new, but it is provides the basic building stones for Section 3, which investigates whether the spoils of learning by doing can be used as a means to build larger emission reduction coalitions. Section 4 then turns to the question what learning and doing and technology transfer do to emissions and incentives to reduce emissions. Section 5 concludes.

2.   Learning by doing and optimal emission reduction trajectories

Let us first consider the case with one player. The player seeks to minimise the net present value of the costs of greenhouse gas emission abatement and climate change:

(1) $$\min_{R_t} C(R_t; H_0, S_0) = \sum_{t=0}^{\infty} \frac{f_t(R_t, H_0) + g_t(S_t)}{(1+\rho)^t}$$

with

$$\frac{\partial f_t}{\partial R_t} > 0, \frac{\partial^2 f_t}{\partial R_t^2} > 0, \frac{\partial f_t}{\partial H_t} < 0, \frac{\partial^2 f_t}{\partial H_t^2} > 0, \frac{\partial H_t}{\partial R_{t-s}} > 0, \frac{\partial^2 H_t}{\partial R_{t-s}^t} < 0, \frac{\partial g_t}{\partial S_t} > 0$$

As usual, t denotes time. R_t is the variable denoting emission reduction as a fraction of emissions; $0 \le R_t \le 1$. S_t is the variable denoting the stock of greenhouse gases in the atmosphere, and S_0 is a constant indicating its value at time zero. H_t is the stock of knowledge. H_0 is the constant indicating its starting value at time zero. Below, we introduce more actors, and H_0 becomes a decision variable, depending on the chosen institutional rules of the game. The net present value of the total costs, C, is the discounted sum of the costs of emission reduction, f_t, and the costs of climate change, g_t. The discount rate is ρ.

The following example is used throughout the paper:

(2) $$f_t(R_t) = \frac{\alpha_t R_t^2}{H_t}$$

(3) $$H_t = \gamma H_{t-1}\sqrt{1+R_{t-1}} = \gamma^t H_0 \prod_{s=1}^{t} \sqrt{1+R_{t-s}} ; t \ge 1$$

(4) $$S_t = \delta S_{t-1} + (1-R_{t-1})E_{t-1} = \delta^t S_0 + \sum_{s=1}^{t} \delta^{s-1}(1-R_{t-s})E_{t-s} ; t \ge 1$$

and

(5) $$g_t(S_t) = \beta_t S_t^2$$

E_t denotes the fixed exogenous assumption for the business as usual emission path. The atmospheric stock, S_t, increases with actual emissions $(1-R_{t-1})E_{t-1}$, and decreases with the natural deterioration of atmospheric carbon dioxide. Greek letters are all parameters: the α in equation (2) reflects the costs of emission abatement; the γ in equation (3) is the exogenous increase in knowledge;[1] the δ in equation (4) denotes the natural decline of carbon in the atmosphere; the β

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[1]   Note that γ differs from the more common AEEI (autonomous energy efficiency improvement); γ drives emission reduction costs only whereas AEEI drives baseline emissions.

in equation (5) reflect the costs of climate change. This framework is very similar to that of Goulder and Mathai (1998); it is also used in Tol (1999b) and Tol *et al.* (2000).

The first-order conditions for this problem are:

$$(6) \qquad \frac{2\alpha_t R_t}{H_t(1+\rho)^t} - \sum_{s=1}^{\infty} \frac{\alpha_{t+s}R_{t+s}^2}{2H_{t+s}(1+\rho)^{t+s}(1+R_t)} - \sum_{s=1}^{\infty}\frac{2\beta_{t+s}S_{t+s}\delta^s E_t}{(1+\rho)^{t+s}} = 0$$

Alternatively,

$$(7) \qquad aR_t - b(1+R_t)^{-1.5} - c = 0$$

Equation (7) is not a very helpful expression, particularly since *a*, *b* and *c* depend on emission reduction at times other than *t*. It is instructive to note that $a \geq 0$, $b \geq 0$, and $c \geq 0$. To a first approximation, this implies that if *c* increases (corresponding to higher impacts of climate change), emission reduction goes up. It also implies that if *b* decreases (corresponding to higher future cost savings induced by current emission abatement), emission reduction goes up. So, the framework makes intuitive sense.

Without learning-by-doing, the first-order conditions would be

$$(8) \qquad \frac{2\alpha_t R_t}{H_t(1+\rho)^t} - \sum_{s=1}^{\infty}\frac{2\beta_{t+s}S_{t+s}\delta^s E_t}{(1+\rho)^{t+s}} = 0$$

Without learning-by-doing, optimal emission reduction would be smaller.[2]

Note the effect of an exogenous increase in knowledge. More knowledge would reduce the costs of emission reduction and decrease the slope of the marginal abatement costs curve. This would increase optimal emission reduction, reducing the costs of climate change. Thus, total costs are reduced.

A similar line of argument does not hold in the case of learning-by-doing. It is true that more knowledge implies less costs implies more emission reduction. However, more knowledge reduces the value of additional knowledge, reducing the incentives to reduce greenhouse gas emissions for knowledge accumulation's sake. Figure 1 demonstrates this graphically for 1 time period, ignoring the feedback of other time periods.

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[2] Note that one cannot draw any conclusions from this. For policy applications, the models with and without learning-by-doing should be calibrated to the same data set. The parameters of the models (α and particularly γ) would be different.

marginal benefits of emission reduction

marginal costs of emission reduction

with learning-by-doing

without learning-by-doing

marginal costs and benefits
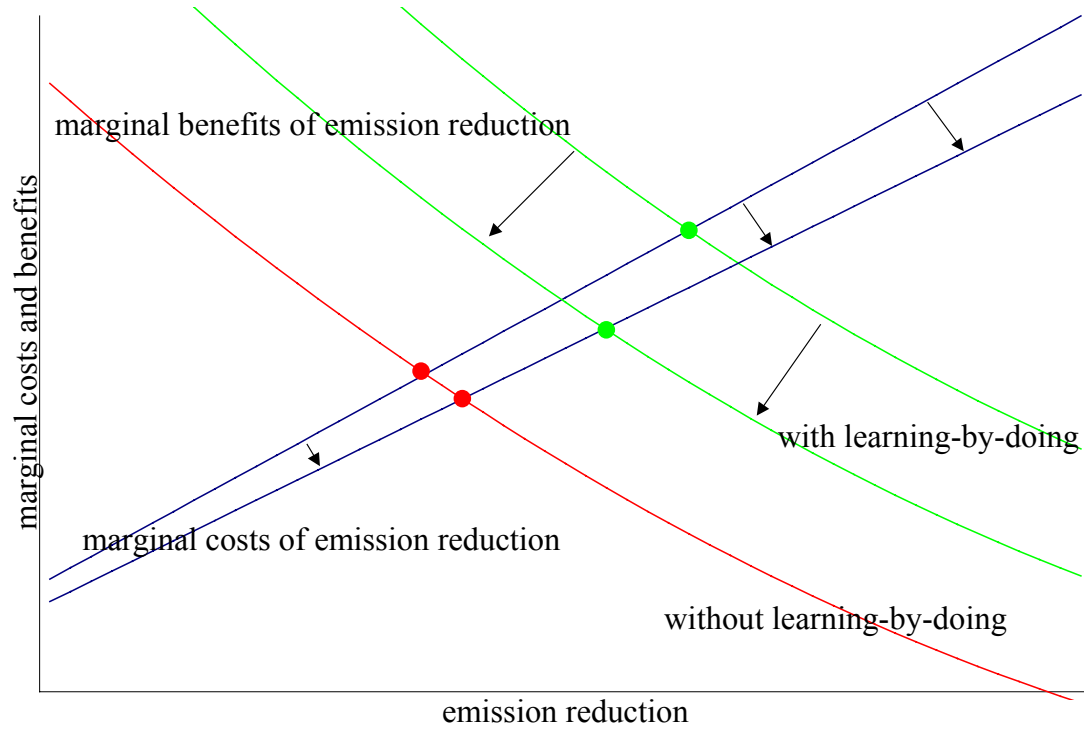
emission reduction

Figure 1. Marginal cost and benefit curves for one time period, ignoring the feedback from other time periods, with and without learning-by-doing. The arrows denote the effect of an exogenous increase in the stock of knowledge. More knowledge decreases the costs of emission reduction, and decreases the benefits of accumulating more knowledge. The impact of knowing more is in later periods, and here presented as a discounted benefit. The dots denote optimal emission reduction levels.

Thus, we have that *more technology does not imply more emission reduction, if technological development is major reason to reduce emissions.*

Therefore, under learning-by-doing, it is not necessarily the case the optimal emission reduction is increasing over time. Without learning-by-doing, optimal emission reduction is increasing with time (Tol, 1999b; Wigley *et al.*, 1996).

3. Cooperation and technology transfer

Even though the effect of exogenously increased knowledge on optimal emission reduction is ambiguous, its effect on total costs is not. It follows from equation (1) that increased knowledge implies reduced costs for unchanged policy:

(9) $\quad \dfrac{\partial C(\overset{1}{R}, H_0, S_0)}{\partial H_0} < 0$

Let R_t^* denote the optimal policy if $H_0 = H^*$. Then

(10) $\quad C(\overset{\vee}{R}{}^*, H^*, S_0) > C(\overset{\vee}{R}{}^*, H^* + h, S_0)$

for any $h > 0$, and after minimising costs according to (1),

(11) $\quad C(\overset{\vee}{R}{}^*, H^* + h, S_0) \geq C(\overset{\vee}{R}{}^{\#}, H^* + h, S_0)$

where $R_t^{\#}$ is the optimal policy for $H_0 = H^* + h$. Thus, exogenously acquired knowledge is unambiguously welfare-improving.

Thus, we have that *more technology means higher welfare.*

Let us now introduce N players, denoted by subscript r, who share the atmosphere and the stock of knowledge. For each player, the problem looks like this.

(12) $\quad \min_{R_{t,r}} C(R_{t,r}; H_0, S_0, R_{t,s \neq r}) = \sum_{t=0}^{\infty} \frac{f_{t,r}(R_{t,r}, H_t) + g_{t,r}(S_t)}{(1+\rho_r)^t}$

with

(13) $\quad f_{t,r}(R_{t,r}, H_t) = \frac{\alpha_{t,r} R_{t,r}^2}{H_t}$

(14) $\quad H_t = \gamma H_{t-1} \prod_{r=1}^{N} (1+R_{t-1,r})^{\omega_{t-1,r}} = \gamma^t \sqrt{H_0} \prod_{s=1}^{t} \prod_{r=1}^{N} (1+R_{t-s,r})^{\omega_{t-s,r}}$

with

(15) $\quad \sum_{r=1}^{N} \omega_{t,r} = 0.5$

The $\omega_{t,r}$ reflects the contribution of region r at time t to the shared knowledge stock H_{t+s}. The ωs sum to ½ to ensure consistency with equation (3).

(16) $\quad S_t = \delta S_{t-1} + \sum_{r=1}^{N} (1 - R_{t-1,r}) E_{t-1,r} = \delta^t S_0 + \sum_{s=1}^{t} \delta^{s-1} \sum_{r=1}^{N} (1 - R_{t-s,r}) E_{t-s,r}$

and

(17) $\quad g_{t,r}(S_t) = \beta_{t,r} S_t^2$

The first-order conditions for this problem are:

(18) $\quad \dfrac{2\alpha_{t,r} R_{t,r}}{H_t (1+\rho_r)^t} - \sum_{s=1}^{\infty} \dfrac{\alpha_{r,t+s} \omega_{t,r} R_{t+s}^2}{H_{t+s}(1+\rho_r)^{t+s}(1+R_{t,r})} - \sum_{s=1}^{\infty} \dfrac{2\beta_{t+s,r} S_{t+s} \delta^s E_{t,r}}{(1+\rho_r)^{t+s}} = 0$

Alternatively,

(19) $\quad a' R_{t,r} - b'(1+R_{t,r})^{-1-\omega_r} - c' = 0$

Equation (19) has properties similar to (7), but b' and c' now also depend on the other players' actions.

Without learning-by-doing, the first-order conditions would be

(20) $\quad \dfrac{2\alpha_{t,r} R_{t,r}}{H_t (1+\rho_r)^t} - \sum_{s=1}^{\infty} \dfrac{2\beta_{t+s,r} S_{t+s} \delta^s E_{t,r}}{(1+\rho_r)^{t+s}} = 0$

Let us now introduce co-operation between the N players. The problem now looks like this.

(21) $\quad \min_{R_{t,r}} C(R_{t,r}; H_0, S_0) \sum_{t=0}^{\infty} \sum_{r=1}^{N} \frac{f_{t,r}(R_{t,r}, H_t) + g_{t,r}(S_{t,r})}{(1+\rho_r)^t}$

with the cost functions and state equations as in (13)-(17).

The first-order conditions for this problem are:

$$(22) \quad \frac{2\alpha_{t,r}R_{t,r}}{H_t(1+\rho_r)^t} - \sum_{s=1}^{\infty}\sum_{r=1}^{N} \frac{\alpha_{r,t+s}\omega_{t,r}R_{t+s}^2}{H_{t+s}(1+\rho_r)^{t+s}(1+R_{t,r})} - \sum_{s=1}^{\infty}\sum_{r=1}^{N} \frac{2\beta_{t+s,r}S_{t+s}\delta^s E_{t,r}}{(1+\rho_r)^{t+s}} = 0$$

Alternatively,

$$(23) \quad a''R_{t,r} - b''(1+R_{t,r})^{-1-\omega_r} - c'' = 0$$

Equation (23) has properties similar to (19), but b'' and c'' are substantially larger, because regions now care about their effect on other regions' climate change impacts and emission reduction costs. Thus, co-operation increases optimal emission reduction. Costs of climate change are, of course, reduced. Costs of emission reduction, per unit, are reduced because of the greater extent of learning-by-doing. The aggregate total costs for all players are lower than without co-operation.

Without learning-by-doing, the first-order conditions would be

$$(24) \quad \frac{2\alpha_{t,r}R_{t,r}}{H_t(1+\rho_r)^t} - \sum_{s=1}^{\infty}\sum_{r=1}^{N} \frac{2\beta_{t+s,r}S_{t+s}\delta^s E_{t,r}}{(1+\rho_r)^{t+s}} = 0$$

Let us now return to the non-co-operative case, 'privatising' the stock of knowledge. For each player, the problem looks like this.

$$(12') \quad \min_{R_{t,r}} C(R_{t,r}; H_0, S_0, R_{t,s\neq r}) = \sum_{t=0}^{\infty} \frac{f_{t,r}(R_{t,r},H_{t,r}) + g_{t,r}(S_{t,r})}{(1+\rho_r)^t}$$

with

$$(25) \quad f_{t,r}(R_{t,r}) = \frac{\alpha_{t,r}R_{t,r}^2}{H_{t,r}}$$

$$(26) \quad H_{t,r} = \gamma H_{t-1,r}(1+R_{t-1,r})^{\omega_{t-1,r}} = \gamma H_0 \prod_{s=1}^{t}(1+R_{t-s,r})^{\omega_{t-s,r}}$$

(for notational convenience, the differences in knowledge at time 0 are collapsed in $\alpha_{0,r}$), with

$$(15) \quad \sum_{r=1}^{N}\omega_{t,r} = 0.5$$

Equations (16) and (17) complete the problem.

The first-order conditions are:

$$(27) \quad \frac{2\alpha_{t,r}R_{t,r}}{H_{t,r}(1+\rho_r)^t} - \sum_{s=1}^{\infty} \frac{\alpha_{r,t+s}\omega_{t,r}R_{t+s}^2}{H_{t+s,r}(1+\rho_r)^{t+s}(1+R_{t,r})} - \sum_{s=1}^{\infty} \frac{2\beta_{t+s,r}S_{t+s}\delta^s E_{t,r}}{(1+\rho_r)^{t+s}} = 0$$

Alternatively,

$$(28) \quad a'''R_{t,r} - b'''(1+R_{t,r})^{-1-\omega_r} - c''' = 0$$

Equation (28) has properties similar to (19), but b''' is substantially larger than b', reducing optimal greenhouse gas emission reduction.

Above, optimal emission reduction trajectories are characterised for a number of cases, that is, with and without international co-operation, with and without learning-by-doing, and with and without a free flow of knowledge between players. Comparison of these cases reveals various insights. Co-operation increases optimal emission reduction, and reduces costs of climate change. The availability of cheap alternatives to fossil fuels reduces costs, in the absence of learning-by-

doing, increases optimal emission abatement over time. With learning-by-doing, the latter finding does not hold: the shape of the optimal emission reduction trajectory is ambiguous.

Equations (9)-(11) establish that an exogenous increase in knowledge unambiguously improves welfare. Equations (14) and (26) behave much the same as equation (3). Thus, access to other players' technologies improves welfare, while granting access does not cost anything (provided that the other players do not substantially increase their emissions after granting access).

Thus, we have that, *since technology is welfare improving, cooperation on technology is individually rational.*

However, we also know that *cooperation on emission reduction is not individually rational*.

If a coalition has the ability to keep policy-induced technology to itself, then members have a smaller incentive to leave the coalition. Non-members have a larger incentive to join the coalition. Thus, in the presence of mechanisms to prevent the diffusion of gainful technology between countries, it is possible to have a greater coalition than in the absence of these mechanisms.

Thus, we have that *making cooperation on emission reduction a condition for technology cooperation reduces free-riding.*

By restricting technology diffusion into countries outside the coalition, greenhouse gas emissions outside the coalition may go up.[3] We further analyse this below, arguing that, for all practical purposes, less technology means more emissions. The coalition may thus hurt itself if it decides to punish defectors.

Furthermore, it is reasonable to assume that if the coalition restricts non-members from using its technology, non-members would react likewise and prevent the coalition from using its technology. This is a sure welfare loss, by (9)-(11).

So, we have established that *if given a choice, countries would cooperate on technology but not on emission reduction.*

Now consider the case of a large coalition, and a small country that is considering whether or not to defect. If it does, it will be denied access to a lot of technology, while its own emissions and technology are insignificant compared to the emissions and technology of the coalition. The coalition may thus retaliate without excessive costs. The question is then whether the threat of restricting technology diffusion is effective? The incentive to defect is unambiguously smaller with potentially restricted technology diffusion than without. Assuming that the coalition exercises its threat, would a country want to leave the coalition?

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[3]   With less clients, the rewards for developing new technologies within the coalition are also weakened; the model ignores this effect.

We cannot answer that question with our analytic model. Therefore, we used a numerical version of the above, programmed in GAMS. The source code is in the Appendix. Figure 1 compares the gains from free-riding (that is, lower emission reduction with almost equal climate impacts) with the losses from less technology (that is, higher emission reduction costs). Figure 1 presents a base case, with all parameters set of central estimates, and a range of sensitivity analyses. It is also presents a maximum scenario, in which all parameters are set to the limits of their ranges so as to maximise the loss of restricted access to technology. Even in the maximum case, the losses due to restricted technology access are less than 3.5% of the gains of free-riding.
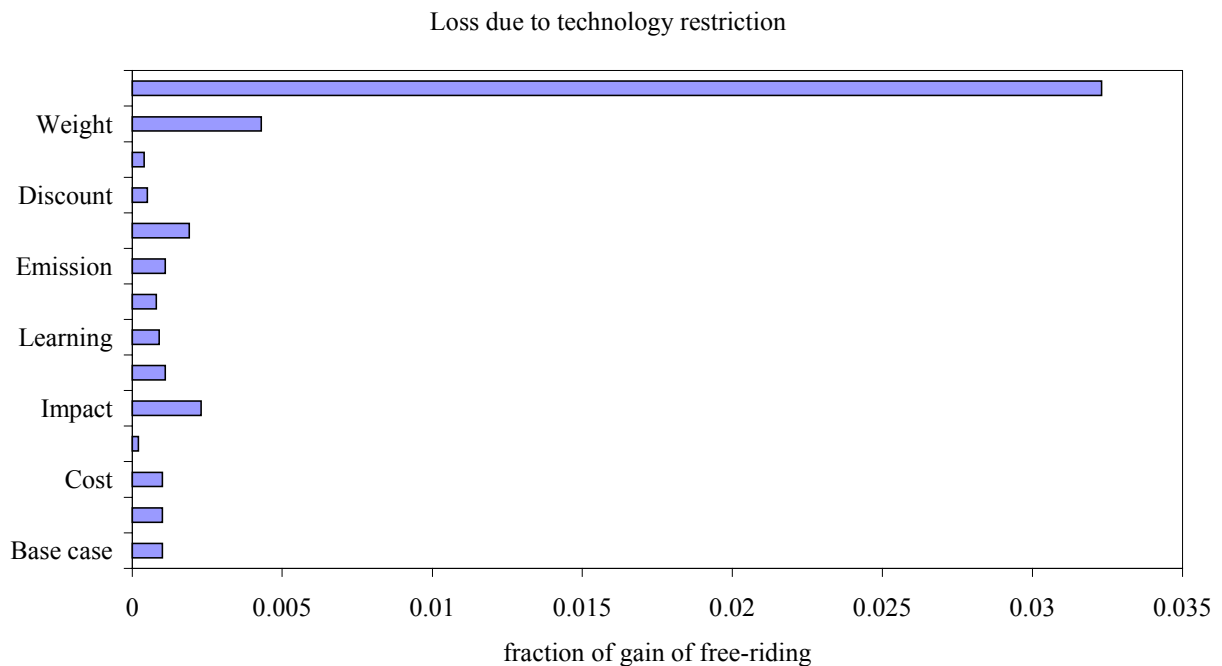
Loss due to technology restriction

Figure 1. The loss of losing access to the grand coalition's technology as a fraction of the gains of free-riding for various parameter choices. In the base case, all parameters are set to their "best guess". Then, from bottom to top, the parameters that control the relative costs of emission reduction, the relative impact of climate change, the rate of learning, the relative baseline emissions, the discount rate, and the welfare weights of the grand coalition and the potential defector, are varied between their high and low values. In the top bar, all parameters are set so that the technology losses are maximised relative to the gains of free-riding. Source: Tol *et al.* (2000).

4. Technology transfer and greenhouse gas emissions
If countries share their technologies, emission reduction costs are reduced. We have seen above this implies that countries want to increase their emission reduction for climate reasons, but reduce their emission reduction for knowledge accumulation's sake. It is not known which of the two effects is stronger.

A further complication is that a country's need to reduce greenhouse gas emissions depends on the emission abatement in other countries. If the benefits of emission reduction are linear in the amount reduced, this feedback is nil. However, if benefits are sub-linear, countries would want to

reduce less (more) if other countries reduce more (less). For all practical purposes, however, the benefits of emission reduction are linear as is shown in Figure 2 (cf. Tol, 1999c).

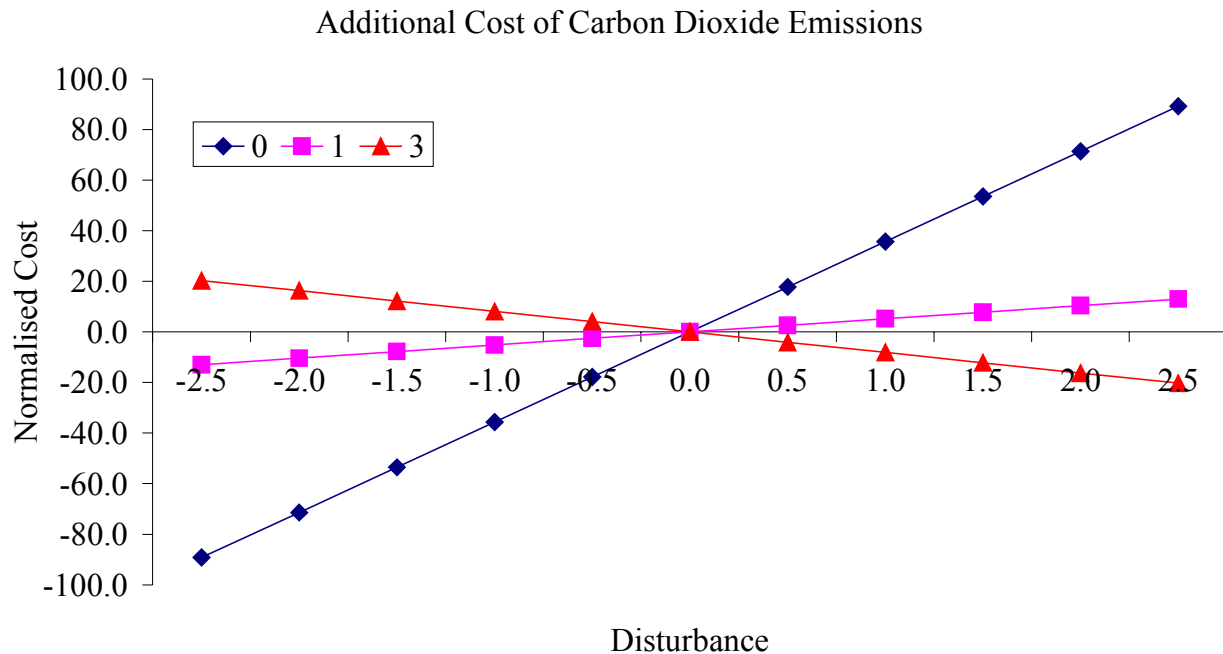Additional Cost of Carbon Dioxide Emissions

Figure 2. The incremental, net present costs of carbon dioxide emissions in the decade 2000-2009 as a function of the size of the emission disturbance for utility discount rates of 0%, 1% and 3%; the estimates are based on *FUND*2.1 (Tol, 2001a,b; Tol and Downing, 2000).

Thus, we have that, *if more technology means less emissions, then technological cooperation is good for climate policy.* That is, technological cooperation on greenhouse gas emission reduction needs to be established, regardless of the question whether countries cooperate on emission abatement itself.

Now consider the case in which only one country hold advanced knowledge of emission reduction technology. That is, other countries can learn from this country, but this country cannot learn from other countries. Above, we assume that all countries can learn from each other. We already established that countries gain from acquiring knowledge, and are in principle prepared to pay for this. The other way around may also be true, that is, a country may want to subsidise the export of its technology. The reason is as follows. If the technology importing countries can be expected to use the technology to reduce emissions, and not use the imports to replace technology acquisition, then this is in the benefit of the technology exporter as well, since climate change and its impacts are reduced.

Thus, we have that *if more technology means less emissions, then technology leaders should subsidise technology transfer.*

Having established that countries benefit from sharing technology – whether or not they cooperation on greenhouse gas emission reduction, and whether or not knowledge is symmetric – it is now time to return to our original question. Does technology transfer help establish cooperation on emission abatement?

We have already seen that linking technology transfer and emission abatement does not help. Suppose that technology sharing reduce emissions in all countries. Thus, with technology sharing, non-cooperative emission control is higher than without technology sharing. Comparing equations (18) and (22), the effect of cooperation is that a country does not set its marginal emission reduction costs equal to its marginal benefits, but rather that a country equals its marginal emission reduction costs to the sum of marginal benefits of all countries. Therefore, if non-cooperative emission control is higher, the distance between cooperation and non-cooperation shrinks, and so do the benefits of free-riding. The reverse is, of course, true if technology sharing increases emissions.

However, a closer look at (18) reveals that, under cooperation, a country does not only heed to its effect on other countries' impacts of climate change, but also to its effect on other countries' emission reduction costs. Since a country's emission reduction effort contributes to other countries' welfare, this is a positive effect, increasing the distance between cooperative and non-cooperative emission control.

Symbolically, let NC denote non-cooperation in emission reduction, and C cooperation. Let NT denote non-cooperation in technology, and T cooperation. Let R denote emission reduction. $R(C,NT) > R(NC,NT)$ and $R(NC,T) > R(NC,NT)$. Thus, $R(C,NT)-R(NC, NT) > R(C,NT)-R(NC,T)$. However, $R(C,T) > R(C,NT)$. Therefore $R(C,T)-R(NC,T) ? R(C,NT)-R(NC,NT)$.

We have shown above that, if more knowledge means reduced emissions, technology cooperation and transfer can act a climate policy instrument in itself. As so many of the findings hinge on the question whether or not emissions go up or down if emission abatement technology is improved, we analyse this further. For this, we use a simpler, two-period model.

Consider two periods, one player. The costs in period 1 follow

(29) $C_1 = \dfrac{\alpha_1}{H_1} R_1^2$

the costs in period 2

(30) $C_2 = \dfrac{\alpha_2}{H_2} R_2^2$

with

(31) $H_2 = H_1 \sqrt{1+R_1}$

The benefits of emission reduction are assumed to be linear in emission reduction (Figure 2). The problem is then

(32) $\min_{R_1,R_2} \dfrac{\alpha_1}{H_1} R_1^2 + \dfrac{1}{1+\delta} \dfrac{\alpha_2}{H_1\sqrt{1+R_1}} R_2^2 - \beta_1 R_1 - \dfrac{1}{1+\delta} \beta_2 R_2$

The first order conditions for the second period are

(33) $\dfrac{2\alpha_2}{(1+\delta)H_1\sqrt{1+R_1}} R_2 - \dfrac{\beta_2}{1+\delta} = 0 \Rightarrow R_2^* = \dfrac{\beta_2 H_1\sqrt{1+R_1}}{2\alpha_2}$

The first order conditions for the first period are

(34) $\quad 2\dfrac{\alpha_1}{H_1}R_1 - \dfrac{\alpha_2 R_2^2}{1+\delta}\dfrac{1}{2H_1\left(1+R_1\right)^{1.5}} - \beta_1 = 0$

Substituting R_2^* for R_2,

(35) $\quad 2\dfrac{\alpha_1}{H_1}R_1 - \dfrac{\beta_2^2 H_1}{8\alpha_2(1+\delta)}\dfrac{1}{\sqrt{1+R_1}} - \beta_1 = 0 \Leftrightarrow \left(2\dfrac{\alpha_1}{H_1}R_1 - \beta_1\right)\sqrt{1+R_1} - \dfrac{\beta_2^2 H_1}{8\alpha_2(1+\delta)} = 0$

In this formulation, more knowledge in period 1 (a higher H_1) implies that optimal emission reduction in periods 1 and 2 is higher. In turn, higher emission reduction in period 1 implies still higher emission reduction in period 2.

If we extend this model to more players, the optimal emission reductions are essentially the same. Diffusion of technology can be modelled as an increase of knowledge for one player, leading to higher emission reduction in that region. The other regions benefit because their climate impacts go down.

The conclusion holds for a more general functional specification as well. Let the costs in period 1 be

(29') $\quad C_1 = \dfrac{\alpha_1}{H_1}R_1^\lambda$ with $\lambda > 0$.

and the costs in period 2

(30') $\quad C_2 = \dfrac{\alpha_2}{H_2}R_2^\lambda$

with

(31') $\quad H_2 = H_1\left(1+R_1\right)^\gamma$ with $0 < \gamma < 1$.

The benefits are again linear in emission reduction. The problem is then

(32') $\quad \min_{R_1,R_2}\dfrac{\alpha_1}{H_1}R_1^\lambda + \dfrac{1}{1+\delta}\dfrac{\alpha_2}{H_1\left(1+R_1\right)^\gamma}R_2^\lambda - \beta_1 R_1 - \dfrac{1}{1+\delta}\beta_2 R_2$

The first order conditions for the second period are

(33') $\quad \dfrac{\lambda\alpha_2}{(1+\delta)H_1\left(1+R_1\right)^\gamma}R_2^{\lambda-1} - \dfrac{\beta_2}{1+\delta} = 0 \Rightarrow R_2^* = \left[\dfrac{\beta_2 H_1\left(1+R_1\right)^\gamma}{\lambda\alpha_2}\right]^{1/\lambda-1}$

The first order conditions for the first period are

(34') $\quad \dfrac{\lambda\alpha_1}{H_1}R_1^{\lambda-1} - \dfrac{\gamma\alpha_2 R_2^\lambda}{1+\delta}\dfrac{1}{H_1\left(1+R_1\right)^{\gamma+1}} - \beta_1 = 0$

Substituting R_2^* for R_2, we get

(35') $\quad \dfrac{\lambda\alpha_1}{H_1}R_1^{\lambda-1} - \dfrac{\gamma\beta_2^{\lambda/\lambda-1}H_1^{1/\lambda-1}}{(1+\delta)\alpha_2^{1/\lambda-1}}(1+R_1)^{\frac{\gamma}{\lambda-1}-1} - \beta_1 = 0$

If $\gamma < \lambda-1$, (35') can be rewritten as

(35'') $\quad \left(\dfrac{\lambda\alpha_1}{H_1}R_1^{\lambda-1} - \beta_1\right)(1+R_1)^{\frac{\lambda-1}{\gamma-\lambda+1}} - \dfrac{\gamma\beta_2^{\lambda/\lambda-1}H_1^{1/\lambda-1}}{(1+\delta)\alpha_2^{1/\lambda-1}} = 0$

In this case, more knowledge in period 1 (a higher H_1) implies that optimal emission reduction in periods 1 and 2 is higher. In turn, higher emission reduction in period 1 implies still higher emission reduction in period 2.

However, if $\gamma > \lambda-1$, no general statement can be made about the relationship between H_1 and R_1.

Now return to the original, less general formulation, with three periods this time. The problem is (36)

$$\min_{R_1,R_2,R_3} \frac{\alpha_1}{H_1} R_1^2 + \frac{1}{1+\delta} \frac{\alpha_2}{H_1\sqrt{1+R_1}} R_2^2 + \frac{1}{(1+\delta)^2} \frac{\alpha_3}{H_1\sqrt{1+R_1}\sqrt{1+R_2}} R_3^2 - \beta_1 R_1 - \frac{1}{1+\delta}\beta_2 R_2 - \frac{1}{(1+\delta)^2}\beta_3 R_3$$

The first order conditions for the third period are

$$(37) \quad \frac{2\alpha_3}{(1+\delta)^2 H_1\sqrt{1+R_1}\sqrt{1+R_2}} R_3 - \frac{\beta_3}{(1+\delta)^2} = 0 \Rightarrow R_3^* = \frac{\beta_3 H_1\sqrt{1+R_1}\sqrt{1+R_2}}{2\alpha_3}$$

The first order conditions for the second period are

$$(38) \quad \frac{2\alpha_2}{(1+\delta)H_1\sqrt{1+R_1}} R_2 - \frac{\alpha_3 R_3^2}{2(1+\delta)H_1\sqrt{1+R_1}(1+R_2)^{1.5}} - \beta_2 = 0$$

Substituting R_3^* for R_3, we get

$$(39) \quad \left(\frac{2\alpha_2}{H_1\sqrt{1+R_1}} R_2 - \beta_2\right)\sqrt{1+R_2} - \frac{\beta_3^2 H_1\sqrt{1+R_1}}{8\alpha_3(1+\delta)} = 0$$

So, period 2 and 3 in the three-period model behave much the same as period 1 and 2 in the two-period model. More knowledge means more emission reduction in period 2 and 3, while more emission reduction in period 2 implies more emission reduction in period 3.

The situation is more complication for period 1. The first order conditions are:

$$(40) \quad \frac{2\alpha_1}{H_1} R_1 - \frac{\alpha_2 R_2^2}{2(1+\delta)H_1(1+R_1)^{1.5}} - \frac{\alpha_3 R_3^2}{2(1+\delta)^2 H_1\sqrt{1+R_2}(1+R_1)^{1.5}} - \beta_1 = 0$$

Substituting R_3^* for R_3, and multiplying by $(1+R_1)^{1.5}$,

$$(41) \quad \frac{2\alpha_1}{H_1} R_1(1+R_1)^{1.5} - \frac{\beta_3^2 H_1\sqrt{1+R_2}}{8(1+\delta)^2\alpha_3} R_1 - \frac{\alpha_2 R_2^2}{2(1+\delta)H_1} - \frac{\beta_3^2 H_1\sqrt{1+R_2}}{8(1+\delta)^2\alpha_3} - \beta_1 = 0$$

From (39), we conclude that R_2^2 is more than linear in H_1. An increase in knowledge would thus increase the constant in (41). The linear and the non-linear components in (41), however, have an opposite dependence on H_1. Therefore, an increase in knowledge would increase emission reduction for some initial R_1, and decrease emission reduction for other values of R_1.

Figure 3 shows the outcomes of a numerical analysis, repeating the above analysis for 200 periods. The model is given in the appendix. Figure 3 shows the changes in optimal emissions in the years 2010, 2050 and 2100 due to a 25% increase in knowledge in the first period. Figure 3 does so for various combinations of the parameters γ and λ. As the analysis above suggests, if $\gamma < \lambda$-1, more knowledge leads to lower emissions. For lower values of λ, however, the effect disappears. This is due to the fact that optimal emission control falls to zero in both the base case and the enhanced knowledge case. In Figure 4, we increase the impact of climate change. As suspected, if $\gamma > \lambda$-1, more knowledge may indeed lead to lower emission control. However, the changes are so small that the effect is negligible.
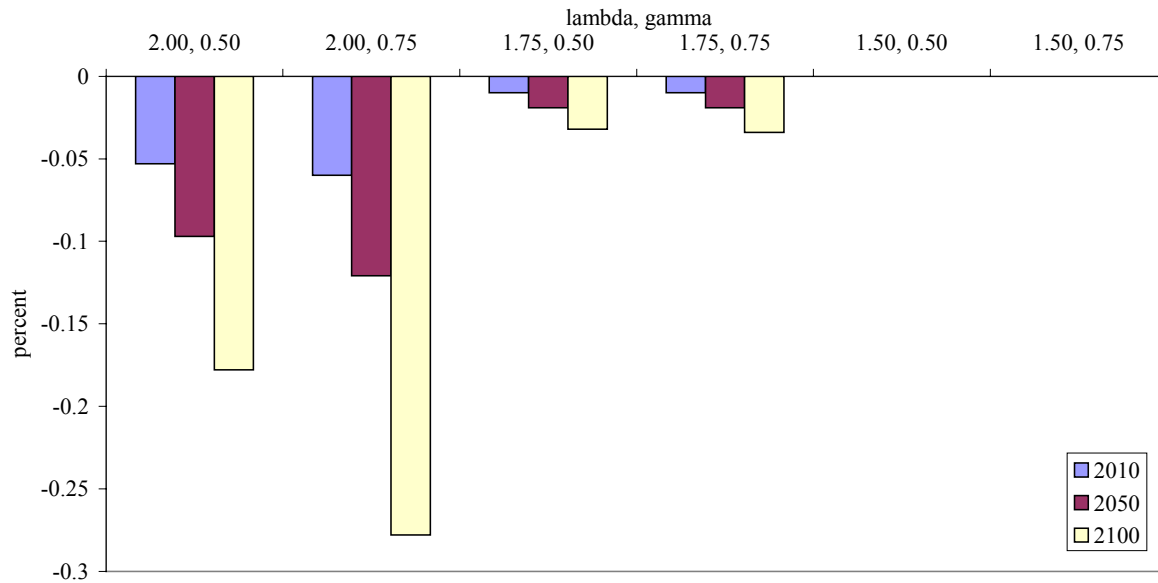

Figure 3. The change in optimal emissions in the years 2010, 2050 and 2100 due to a 25% increase in knowledge, expressed as a percentage of optimal emissions without that knowledge increase, for various combinations of the parameters λ and γ of equation (36) extended to 200 periods.
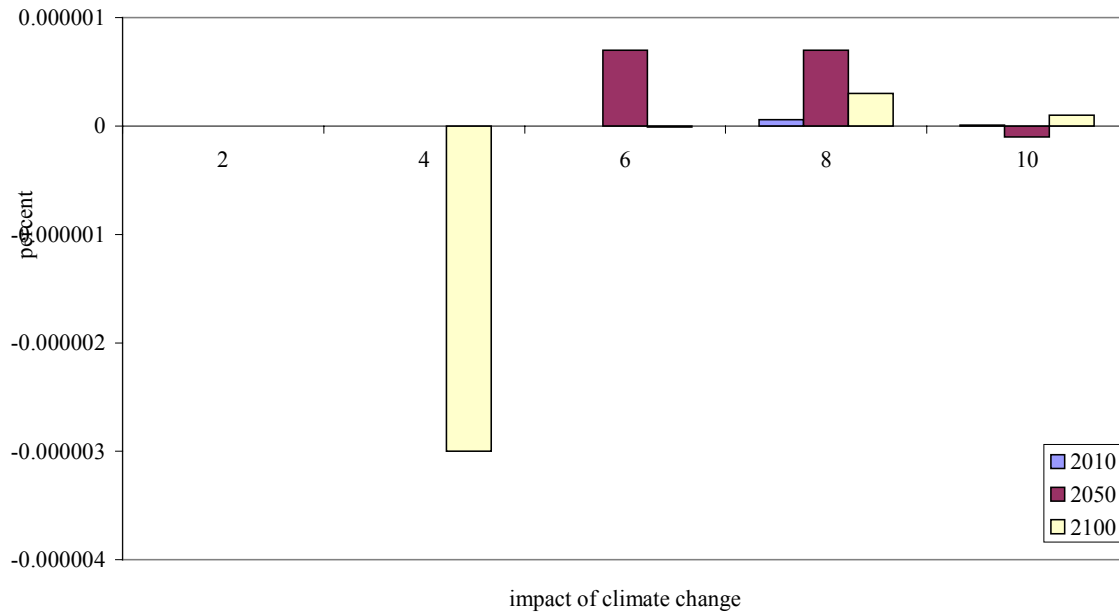
Figure 4. The change in optimal emissions in the years 2010, 2050 and 2100 due to a 25% increase in knowledge, expressed as a percentage of optimal emissions without that knowledge increase, for parameters $\lambda=1.50$ and $\gamma=0.75$ in equation (36) extended to 200 periods, as a function of the impact of climate change.

5.   Conclusions

In this paper, we establish that technology developed through greenhouse gas emission reduction policy cannot act as a stabilizer of emission reduction coalitions. The reason is that such technology, like other types of technologies, is a club good. Countries like to cooperate on technological development and share their knowledge. Restricting access to technology is not a credible threat, because potential retaliation would hurt. The threat may also be ineffective, that is, the gains of free riding on emission reduction may outweigh the losses of restricted access to technology.

Technological cooperation may well be good for emission reduction policy. We show that if technologies help combat global externalities, countries should actually subsidise technology transfer. We argue that technological cooperation does not necessarily reduce free-riding incentives on emission abatement. However, technological cooperation is likely to help reduce greenhouse gas emissions.

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* EndoCoal
* Richard S.J. Tol, July 9, 1999

SETS
T               time periods                                    /1*200/
TF(T)           first period
TL(T)           last period

SCALARS
A1              costs of emission reduction player 1        /2/
A2              costs of emission reduction player 2        /2/
B1              costs of climate change player 1            /0.02/
B2              costs of climate change player 2            /0.02/
C1              LbD parameter player 1                      /0.45/
C2              LbD parameter player 2                      /0.06/
D1              secondary benefits player 1                 /0.001/
D2              secondary benefits player 2                 /0.006/
RHO             discount rate                               /0.03/
DELTA           carbon uptake                               /0.01/
S0              initial stock of carbon                     /350/
E01             initial emissions player 1                  /2.0/
E02             initial emissions player 2                  /0.2/
DGE1            decline of growth rate of emissions player 1    /0.995/
DGE2            decline of growth rate of emissions player 2    /0.995/
GE10            initial growth rate of emissions player 1   /0.01/
GE20            initial growth rate of emissions player 2   /0.01/
H0              initial knowledge stock                     /1/
H10             initial knowledge stock player 1            /1/
H20             initial knowledge stock player 2            /1/

PARAMETERS
GE1(T)          growth rate of emissions player 1
GE2(T)          growth rate of emissions player 2
E1(T)           level of emissions player 1
E2(T)           level of emissions player 2
DISC(T)         discount factor
NP1
NP2
NP;

TF(T)      = YES$(ORD(T) EQ 1);
TL(T)      = YES$(ORD(T) EQ CARD(T));

DISPLAY TF, TL;

GE1(T)     = GE10*DGE1**ORD(T);
GE2(T)     = GE20*DGE2**ORD(T);
E1(T)      = E01*(1+GE1(T))**ORD(T);
E2(T)      = E02*(1+GE2(T))**ORD(T);
DISC(T)    = (1+RHO)**(-ORD(T));
```

```
DISPLAY GE1, GE2, E1, E2, DISC;

VARIABLES
R1(T)            emission control rate player 1
R2(T)            emission control rate player 2
S(T)             carbon stock
H1(T)            knowledge stock player 1
H2(T)            knowledge stock player 2
H(T)             knowledge stock player 1 + 2
TC1(T)           total costs player 1
TC2(T)           total costs player 2
NPVC1            net present costs player 1
NPVC2            net present costs player 2
NPVC             net present costs player 1 + 2;

POSITIVE VARIABLES
R1, R2, H1, H2, H, S, TC1, TC2;

EQUATIONS
UTIL             objective function
ETC              total costs
HIN              knowledge stock initialization
H1IN
H2IN
HEQ              knowledge stock evolution
HEQQ
H1EQ
H2EQ
SIN              carbon stock initialization
SEQ              carbon stock evolution
TC1RD            total costs player 1 restricted diffusion
TC1FD            total costs player 1 free diffusion
TC2RD            total costs player 2 restricted diffusion
TC2FD            total costs player 2 free diffusion
NPV              net present value
NPV1
NPV2;

HIN(TF)..        H(TF) =E= H0;
H1IN(TF)..       H1(TF) =E= H10;
H2IN(TF)..       H2(TF) =E= H20;
HEQ(T+1)..       H(T+1) =E= H(T)*(1+R1(T))**C1*(1+R2(T))**C2;
HEQQ(T+1)..      H(T+1) =E= H(T);
H1EQ(T+1)..      H1(T+1) =E= H1(T)*(1+R1(T))**C1;
H2EQ(T+1)..      H2(T+1) =E= H2(T)*(1+R2(T))**C2;

SIN(TF)..        S(TF) =E= S0;
SEQ(T+1)..       S(T+1) =E= S(T)-DELTA*(S(T)-S0)+(1-R1(T))*E1(T)+(1-
R2(T))*E2(T);

TC1RD(T)..       TC1(T) =E= A1*R1(T)*R1(T)/H1(T) - D1*R1(T)**0.5 +
B1*(S(T)/S0)*(S(T)/S0);
TC1FD(T)..       TC1(T) =E= A1*R1(T)*R1(T)/H(T)  - D1*R1(T)**0.5 +
B1*(S(T)/S0)*(S(T)/S0);
TC2RD(T)..       TC2(T) =E= A2*R2(T)*R2(T)/H2(T) - D2*R2(T)**0.5 +
B2*(S(T)/S0)*(S(T)/S0);
```

```
TC2FD(T)..        TC2(T) =E= A2*R2(T)*R2(T)/H(T)  - D2*R2(T)**0.5 +
B2*(S(T)/S0)*(S(T)/S0);

NPV1..            NPVC1  =E= SUM(T,TC1(T)*DISC(T));
NPV2..            NPVC2  =E= SUM(T,TC2(T)*DISC(T));
NPV..             NPVC =E= SUM(T,(10*TC1(T)+TC2(T))*DISC(T));

R1.UP(T)  = 0.99999;     R1.LO(T)  = 0.00001;
R2.UP(T)  = 0.99999;     R2.LO(T)  = 0.00001;
H.LO(T) = 0.01; H1.LO(T) = 0.01; H2.LO(T) = 0.01;

option iterlim  = 99999;
option reslim   = 99999;
option solprint = off;
option limrow   = 0;
option limcol   = 0;

MODEL COOQ /HIN, HEQQ, SIN, SEQ, TC1FD, TC2FD, NPV1, NPV2, NPV/;

SOLVE COOQ MINIMIZING NPVC USING NLP;

SOLVE COOQ MINIMIZING NPVC USING NLP;

MODEL COOP /HIN, HEQ, SIN, SEQ, TC1FD, TC2FD, NPV1, NPV2, NPV/;

SOLVE COOP MINIMIZING NPVC USING NLP;

SOLVE COOP MINIMIZING NPVC USING NLP;

NP1 = 1000000*NPVC1.L;
NP2 = 1000000*NPVC2.L;
NP  = 1000000*NPVC.L;

DISPLAY NP1, NP2, NP;

DISPLAY R1.L, R2.L, S.L, H.L, TC1.L, TC2.L, NPVC1.L, NPVC2.L, NPVC.L;

MODEL NCFD /HIN, HEQ, SIN, SEQ, TC1FD, TC2FD, NPV1, NPV2, NPV/;

R1.UP(T) = R1.L(T); R1.LO(T) = R1.L(T);

SOLVE NCFD MINIMIZING NPVC2 USING NLP;

SOLVE NCFD MINIMIZING NPVC2 USING NLP;

R2.UP(T) = R2.L(T); R2.LO(T) = R2.L(T);

SOLVE NCFD MINIMIZING NPVC1 USING NLP;

SOLVE NCFD MINIMIZING NPVC1 USING NLP;

R1.UP(T) = R1.L(T); R1.LO(T) = R1.L(T);

SOLVE NCFD MINIMIZING NPVC2 USING NLP;

R2.UP(T) = R2.L(T); R2.LO(T) = R2.L(T);

SOLVE NCFD MINIMIZING NPVC1 USING NLP;
```

```
R1.UP(T) = R1.L(T); R1.LO(T) = R1.L(T);

SOLVE NCFD MINIMIZING NPVC2 USING NLP;

R2.UP(T) = R2.L(T); R2.LO(T) = R2.L(T);

SOLVE NCFD MINIMIZING NPVC1 USING NLP;

R1.UP(T) = R1.L(T); R1.LO(T) = R1.L(T);

SOLVE NCFD MINIMIZING NPVC2 USING NLP;

R2.UP(T) = R2.L(T); R2.LO(T) = R2.L(T);

SOLVE NCFD MINIMIZING NPVC1 USING NLP;

NP1 = 1000000*NPVC1.L;
NP2 = 1000000*NPVC2.L;
NP  = 1000000*NPVC.L;

DISPLAY NP1, NP2, NP;

DISPLAY R1.L, R2.L, S.L, H.L, TC1.L, TC2.L, NPVC1.L, NPVC2.L, NPVC.L;

MODEL NCRD /H1IN, H2IN, H1EQ, H2EQ, SIN, SEQ, TC1RD, TC2RD, NPV1, NPV2, NPV/;

R1.UP(T) = R1.L(T); R1.LO(T) = R1.L(T);

SOLVE NCRD MINIMIZING NPVC2 USING NLP;

SOLVE NCRD MINIMIZING NPVC2 USING NLP;

R2.UP(T) = R2.L(T); R2.LO(T) = R2.L(T);

SOLVE NCRD MINIMIZING NPVC1 USING NLP;

SOLVE NCRD MINIMIZING NPVC1 USING NLP;

R1.UP(T) = R1.L(T); R1.LO(T) = R1.L(T);

SOLVE NCRD MINIMIZING NPVC2 USING NLP;

R2.UP(T) = R2.L(T); R2.LO(T) = R2.L(T);

SOLVE NCRD MINIMIZING NPVC1 USING NLP;

R1.UP(T) = R1.L(T); R1.LO(T) = R1.L(T);

SOLVE NCRD MINIMIZING NPVC2 USING NLP;

R2.UP(T) = R2.L(T); R2.LO(T) = R2.L(T);

SOLVE NCRD MINIMIZING NPVC1 USING NLP;

R1.UP(T) = R1.L(T); R1.LO(T) = R1.L(T);

SOLVE NCRD MINIMIZING NPVC2 USING NLP;
```

```
R2.UP(T) = R2.L(T); R2.LO(T) = R2.L(T);


SOLVE NCRD MINIMIZING NPVC1 USING NLP;


NP1 = 1000000*NPVC1.L;
NP2 = 1000000*NPVC2.L;
NP  = 1000000*NPVC.L;


DISPLAY NP1, NP2, NP;


DISPLAY R1.L, R2.L, S.L, H1.L, H2.L, TC1.L, TC2.L, NPVC1.L, NPVC2.L, NPVC.L;



* EndoCoal2
* Richard S.J. Tol, November 5, 2000

SETS
T               time periods                                    /1*200/
TF(T)           first period
TL(T)           last period

SCALARS
A1              costs of emission reduction player 1            /2/
B1              costs of climate change player 1                /0.1/
C1              LbD parameter player 1                          /0.5/
D1              curvature                                       /2/
RHO             discount rate                                   /0.03/
DELTA           carbon uptake                                   /0.01/
S0              initial stock of carbon                         /350/
E01             initial emissions player 1                      /2.0/
DGE1            decline of growth rate of emissions player 1    /0.995/
GE10            initial growth rate of emissions player 1       /0.01/
H10             initial knowledge stock player 1                /1/

PARAMETERS
GE1(T)          growth rate of emissions player 1
E1(T)           level of emissions player 1
Ea(T)
Eb(T)
Ec(T)
Eab(T)
Ebc(T)
DISC(T)         discount factor
LBD
Hadd
NP1;

TF(T)       = YES$(ORD(T) EQ 1);
TL(T)       = YES$(ORD(T) EQ CARD(T));


DISPLAY TF, TL;


GE1(T)      = GE10*DGE1**ORD(T);
E1(T)       = E01*(1+GE1(T))**ORD(T);
DISC(T)     = (1+RHO)**(-ORD(T));


DISPLAY GE1, E1, DISC;
```

```
VARIABLES
R1(T)            emission control rate player 1
S(T)             carbon stock
H1(T)            knowledge stock player 1
TC1(T)           total costs player 1
NPVC1            net present costs player 1;

POSITIVE VARIABLES
R1, H1, S, TC1;

EQUATIONS
UTIL             objective function
ETC              total costs
H1IN             knowledge stock initialization
H1EQ             knowledge stock evolution
SIN              carbon stock initialization
SEQ              carbon stock evolution
TC1E             total costs player 1 restricted diffusion
NPV1;

H1IN(TF)..       H1(TF) =E= Hadd*H10;
H1EQ(T+1)..      H1(T+1) =E= H1(T)*(1+LBD*R1(T))**C1;

SIN(TF)..        S(TF) =E= S0;
SEQ(T+1)..       S(T+1) =E= S(T)-DELTA*(S(T)-S0)+(1-R1(T))*E1(T);

TC1E(T)..        TC1(T) =E= A1*R1(T)**D1/H1(T) + B1*(S(T)/S0)*(S(T)/S0);
NPV1..           NPVC1  =E= SUM(T,TC1(T)*DISC(T));

R1.UP(T)  = 0.9999;     R1.LO(T)  = 0.0001;
H1.LO(T) = 0.01;

option iterlim  = 99999;
option reslim   = 99999;
option solprint = off;
option limrow   = 0;
option limcol   = 0;

MODEL NCRD /H1IN, H1EQ, SIN, SEQ, TC1E, NPV1/;

LBD = 0.00;
Hadd = 1;
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
Ea(T) = (1-R1.L(T))*E1(T);
LBD = 0.33;
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
LBD = 0.67;
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
LBD = 1.00;
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
```

```
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
Eb(T) = (1-R1.L(T))*E1(T);

NP1 = 1000000*NPVC1.L;

DISPLAY NP1, R1.L, S.L, H1.L, TC1.L, NPVC1.L;

Hadd = 1.00;
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
SOLVE NCRD MINIMIZING NPVC1 USING NLP;
Ec(T) = (1-R1.L(T))*E1(T);

NP1 = 1000000*NPVC1.L;

DISPLAY NP1, R1.L, S.L, H1.L, TC1.L, NPVC1.L;

Eab(T) = 100*(Ea(T)-Eb(T))/Ea(T);
Ebc(T) = 100*(Eb(T)-Ec(T))/Eb(T);
DISPLAY E1, Ea, Eb, Ec, Eab, Ebc;
```