TECHNOLOGY DIFFUSION AND THE STABILITY OF CLIMATE COALITIONS

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2 February 2000

Policy makers summary

Free-riding is a major problem for international climate policy. A country can take advantage of other countries' emission reduction without contributing to abatement policies itself. Game theory suggests that issue linkage may help to overcome free-riding. Earlier studies suggest that if negotiations on greenhouse gas emission reduction are coupled to negotiation on technology transfer, the incentives to co-operate increase. This study confirms that finding. A country has less reason to free-ride if free-riding implies that the countries looses access to desirable, foreign technologies. We also show that, in many cases, it hurts to deny another country access to domestic technologies, if that country retaliates by withholding its technologies. We further show that the losses of withholding abatement technologies are small relative to the gains of free-riding. So, linking greenhouse gas emission reduction with technology diffusion helps to deter free-riding, but only a little bit, and only if the two issues are automatically linked.

Abstract

Countries have little incentive to co-operate with one another in case each of them is seeking to optimally control greenhouse gas emissions. Free-riding erodes the global coalition. Capital transfers are not necessarily a solution to this, because of the size of transfers, the direction of the transfers, and large stakes involved which could well render utility untransferable.

This paper investigates whether restrictions on the diffusion of carbon-saving technologies (e.g., through discriminate patenting) can be instrumental in establishing more co-operation between nations. The result is ambiguous. It is shown that restricting technology diffusion is a real threat, that is, it unambiguously hurts the potential defector. It is shown that, by the same token, it is an unambiguously incredible threat, that is, it hurts the coalition to exercise the technology restriction. It is argued that the threat is more likely to be effective if the defector is small relative to the coalition.

1. *Introduction*

This paper is a bit at odds with the typical paper on climate economics. Targets for emission reduction are not set exogenously – say, by divine revelation to a national lab – but are determined endogenously, that is, by seeking the greatest good to the greatest number. Nordhaus (1991) pioneered this.

The world is not assumed to be ruled by a benevolent dictator. Instead, the world is split into several sovereign entities, which may choose to co-operate with one another or not. It is well-documented that mitigation of climate change has every characteristic of a public good (Barrett, 1990, 1994; Carraro, 1998; Carraro and Moricone, 1997; Carraro and Siniscalco, 1992; Chen, 1997; Eyckmans *et al.*, 1993; Hoel, 1994; Nordhaus and Yang, 1996; Tol, 1997, 1999a,b). The deviation of national and global welfare is such that free-riding would be wide-spread. If each country would seek to further its own interests, greenhouse gas emission reduction would fall substantially below the global optimal course. Indeed, Nordhaus and Yang (1996) and Tol (1997, 1999a,b) show that a nonco-operative emission abatement policy is hard to distinguish from no policy at all.

The standard answer of game theory to free-riding is capital transfers (Friedman, 1991; Gibbons, 1992). The gains of co-operation are sufficient to set up a system of side payments which compels each player not to defer from the grand coalition. This is true for any game, as long as utility is transferable.

It does not work for climate change, for two reasons. Firstly, the poor are more vulnerable to climate change than the rich (Fankhauser, 1995; Tol, 1995). Therefore, the poor are more interested in greenhouse gas emission reduction than the rich.[1] This implies that capital should be transferred from the poor to the rich. This is unlikely. Secondly, differences in income between countries are so large that the proper metric of analysis is utility. Utility is not transferable. Suppose the poor were willing to compensate the rich for greenhouse gas emission reduction. Their utility gains would be insufficient to convince the rich. The utility gains of the poor would be expressed in their monetary equivalent, and then transferred to the rich. These side payments would then be judged as to their addition to the utility of the rich, and considered insufficient (Tol, 1997).

The starting point of this paper is a world wanting to reduce greenhouse gas emissions, but trapped in the prisoner's dilemma. A way out would be to link climate change to another issue. Issue linkage is known to be able to overcome free-riding. The principle is simple. If A wants B to co-operate on issue 1, and B wants A to co-operate on issue 2, then A and B want to co-operate on issue 1+2. Carraro and Siniscalco (1992, 1993) and Cesar and de Zeeuw (1994) give excellent, generic insights into issue linkage in international environmental policy.

Issues to link to climate change are not readily available. The poor have little to offer to the rich, and in the few cases they do, capital transfers would do the job. Therefore,

[1] This is not observed in reality. One reason is that many poor nations cannot afford the luxury of worrying about a remote problem such as climate change. Another reason may be the historical responsibility of the OECD for the problem of climate change. Neither effect can be easily captured in the type of model used here. It can be observed, however, that most rich countries are not in a great hurry to reduce their emissions of greenhouse gases, despite all the rhetoric to that effect.

in this paper, the issue linked is internal and dynamic. That is, positive spin-offs of emission abatement are used to entice potential free-riders.

Greenhouse gas emission reduction would not only slow global warming, it would also spur research and development of technologies to do so at lower costs. If emission abatement becomes cheaper, more emissions would be reduced. Technology is somewhat of a public good as well. Patents help the developer to capture the R&D costs plus a profit, but the technology is free to be used by anybody. This paper investigates whether technological development induced by greenhouse gas emission reduction can help international co-operation. The thought is simple. If technologies induced by emission abatement within a coalition can only be used by members of that coalition, any country that leaves the coalition suffers a welfare loss for being comparatively restrained in the available technology.

The larger part of the argument regards learning-by-doing rather than investments in research and development. The reason is that the players in the game are governments. Government R&D money is best spent on fundamental research. In energy and transport, engineering, diffusion and marketing are needed. This is best left to companies, so instigated by government through prices or standards (Gomulka, 1990).[2] In this context, learning-by-doing is thus best interpreted as technological progress brought about by non-government actors in response to government policy.

Carraro and Siniscalco (1996) and Katsoulacos (1996) look at the same issue, linkages between international diffusion of technology and environmental externalities. Their models differ from the one used here. Both distinguish between firms and governments, and let firms invest in R&D to further technology. Katsoulacos (1996) also considers R&D subsidies. Thus, they explicitly represent what we assume implicitly in learning-by-doing. Carraro and Siniscalco (1996) consider generic technology whereas Katsoulacos (1996) and this paper consider abatement-specific technology. Carraro and Siniscalco (1996) and Katsoulacos (1996) consider a static framework whereas we consider a dynamic one. In all three cases, the game is static, however. Carraro and Siniscalco (1996) and Katsoulacos (1996) reach essentially the same conclusion as we do: A link between greenhouse gas emission reduction and technology transfer helps building larger coalitions. However, we also look at the case in which the link is not automatic, and so cast doubt on this conclusion. In a more general set-up, Conconi and Perroni (2000) show the difference between automatic issue linkage and optional issue linkage.

2. *Analytical framework*

2.1. One player

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

with

[2] However, technology is partly a public and partly a private good. Governments may still need to step in with, say, R&D subsidies so as further the provision of (intertemporal) positive externalities.

$\vec{R} = (R_0, R_1, R_2, ...)$
and

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

The following example is used throughout the paper:

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

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

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

and

(5) $$g_t(S_t) = b_t S_t^2$$

R_t denotes emission reduction as a fraction of emissions; 0 R_t 1. E_t are (fixed) business as usual emissions; E_t is a parameter. S_0 denotes the stock of greenhouse gases in the atmosphere; S_0 is its value at time zero, and treated as a parameter. S_t increases with actual emission (1-R_{t-1})E_{t-1} and decrease with natural deterioration of atmospheric carbon dioxide. H_t is the stock of knowledge. H_0 is a parameter here, but a 'variable' below. t denotes time. Greek letters are parameters; the ã in equation (3) is the exogenous increase in knowledge. This framework is very similar to that of Goulder and Mathai (1998).

The first-order conditions for this problem are:

(6) $$\frac{2a_t R_t}{H_t(1+r)^t} - \sum_{s=1}^{\infty} \frac{a_{t+s} R_{t+s}^2}{2H_{t+s}(1+r)^{t+s}(1+R_t)} - \sum_{s=1}^{\infty} \frac{2b_{t+s} S_{t+s} d^s E_t}{(1+r)^{t+s}} = 0$$

Alternatively,

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

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 0, b 0, and c 0. To a first approximation, this implies that if c increases (i.e., higher impacts of climate change), emission reduction should go up. It also implies if b decreases (i.e., higher future cost savings induced by current emission abatement), emission reduction should go up. So, the framework, although messy, makes intuitive sense.

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

(8) $$\frac{2a_t R_t}{H_t(1+r)^t} - \sum_{s=1}^{\infty} \frac{2b_{t+s} S_{t+s} d^s E_t}{(1+r)^{t+s}} = 0$$

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

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.

This line of argumentation is more involved with learning-by-doing, but the conclusion is the same. 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 times.

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:

$$(9)\qquad \frac{\partial C(\vec{R}, H_0, S_0)}{\partial H_0} < 0$$

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

$$(10)\qquad C(\vec{R}^*, H^*, S_0) > C(\vec{R}^*, H^* + h, S_0)$$

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

$$(11)\qquad C(\vec{R}^*, H^* + h, S_0) \geq C(\vec{R}^\#, H^* + h, S_0)$$

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

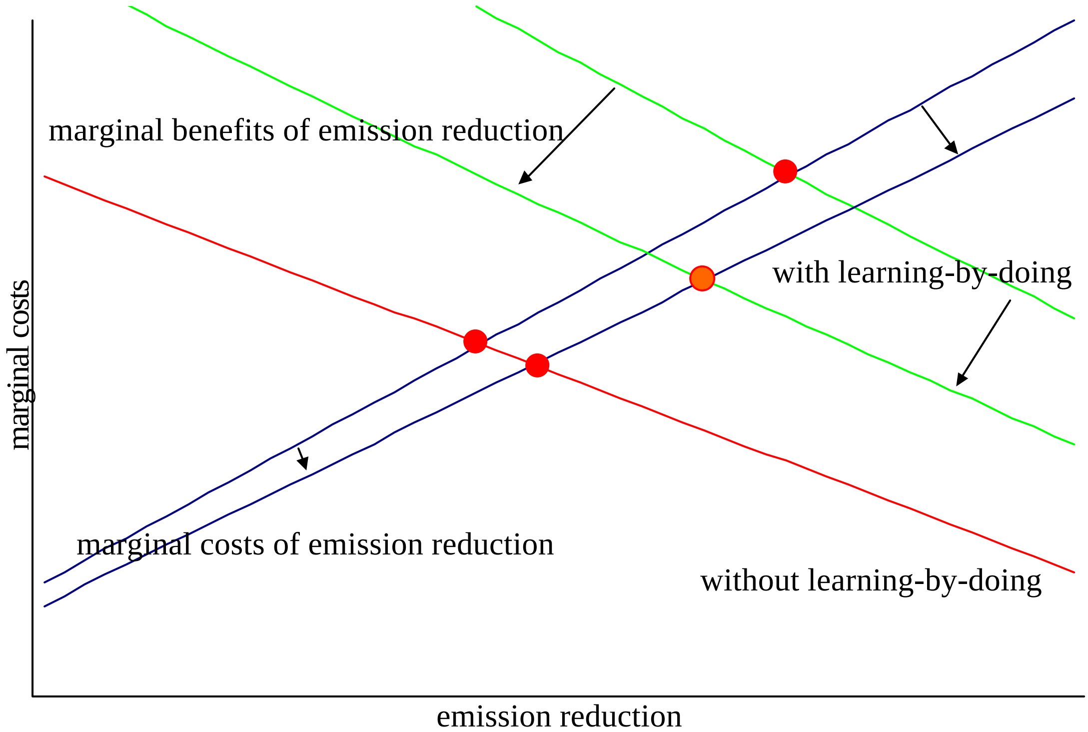

Figure 1. Marginal cost and benefit curves for one time period, with and without learning-by-doing. The arrows denote the effect of the exogenous increase in knowledge would have. The dots denote optimal emission reduction levels.

2.2. No co-operation, free technology diffusion

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.

$$(12)\qquad \min_{R_{t,r}} \sum_{t=0}^{\infty} \frac{f_{t,r}(R_{t,r}, H_t) + g_{t,r}(S_t)}{(1+r_r)^t}$$

with

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

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

with

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

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

and

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

The first-order conditions for this problem are:

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

Alternatively,

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

Equation (19) has properties similar to (7), but *b'* and *c'* now also depend on the other players' actions, specifically, what this player knows or assumes about the other players' actions.[3]

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

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

2.3. Co-operation, free technology diffusion

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

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

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

The first-order conditions for this problem are:

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

Alternatively,

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

Equation (23) has properties similar to (19), but *b''* and *c''* are substantially larger. 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

[3] In the rest of the model, perfect knowledge is assumed. Thus, it would be natural to assume that each player perfectly knows the other players' motivations and actions. However, this assumption is not necessary for the argument to hold.

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) $$\frac{2a_{t,r}R_{t,r}}{H_t(1+r_r)^t}-\sum_{s=1}^{\infty}\sum_{r=1}^{N}\frac{2b_{t+s,r}S_{t+s}d^s E_{t,r}}{(1+r_r)^{t+s}}=0$$

2.4. No co-operation, restricted technology diffusion

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

(12’) $$\min_{R_{t,r}}\sum_{t=0}^{\infty}\frac{f_{t,r}(R_{t\,r},H_{t,r})+g_{t,r}(S_{t,r})}{(1+r_r)^t}$$

with

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

(26) $$H_{t,r}=gH_{t-1,r}(1+R_{t-1,r})^{w_{t-1,r}}=gH_0\prod_{s=1}^{t}(1+R_{t-s,r})^{w_{t-s,r}}$$

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

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

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

The first-order conditions are:

(27) $$\frac{2a_{t,r}R_{t,r}}{H_{t,r}(1+r_r)^t}-\sum_{s=1}^{\infty}\frac{a_{r,t+s}w_{t,r}R_{t+s}^2}{H_{t+s,r}(1+r_r)^{t+s}(1+R_{t,r})}-\sum_{s=1}^{\infty}\frac{2b_{t+s,r}S_{t+s}d^s E_{t,r}}{(1+r_r)^{t+s}}=0$$

Alternatively,

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

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

3. Coalitions with and without technology diffusion

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 the 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 and, in the absence of learning-by-doing, increases optimal emission abatement. With learning-by-doing, the latter finding does not hold.

The novel insight is this. 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 (provided that the other players do not substantially increase their emissions). 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 learning-by-doing and of mechanisms to prevent the diffusion of technology between countries, it is possible to have a greater coalition than in the absence of these mechanisms.

There is also a caveat. The size of the bonus (new technologies) and the reward (reduced costs of greenhouse gas emission reduction and climate change) both depend on the seriousness of climate change. If climate change is not considered to be a serious problem, the effect of learning-by-doing and restricted technology diffusion is small.

Another caveat is the following. By restricting technology diffusion to the coalition, greenhouse gas emission abatement outside the coalition may be reduced.[4] The welfare implications for the coalition of restricting diffusion are not clear. It is reasonable to assume, however, that if the coalition restricts non-members from using its technology, non-members would react likewise. This is a sure welfare loss, by (9)-(11).

The game and its pay-offs are outlined in Figure 2, with player A being the potential defector and player C the coalition. The game is in two stages. Before the beginning of time, the players choose whether or not to co-operate, and whether or not to restrict the diffusion of technology. This decision is based on the pay-off in the second stage. In the second stage, at the beginning of time, the players optimise their emission reduction strategies, either in a dynamic control problem (full co-operation) or in a open-loop Nash equilibrium (no co-operation), given the rules of engagement.

Figure 2. Pay-off matrix[a]

		A		
		CP-FD	NC-FD	NC-RD
	CP-FD	c_{11}, a_{11}	c_{12}, a_{12}	c_{13}, a_{13}
C	NC-FD	c_{21}, a_{21}	c_{22}, a_{22}	c_{23}, a_{23}
	NC-RD	c_{31}, a_{31}	c_{32}, a_{32}	c_{33}, a_{33}

[a] A denotes the potential defector, a its pay-off; C denotes the coalition, c its pay-off; CP denotes co-operation; NC denotes non-co-operation; FD denotes free diffusion of technology; RD denotes restricted diffusion of technology.

The following can be stated about the pay-offs in Figure 2:

- Co-operation and free technology are the socially and individually preferred cases: $a_{33} < a_{22} < a_{11}$ and $c_{33} < c_{22} < c_{11}$
- Player A has an incentive to free-ride: $a_{11} < a_{12}$
- Player C can punish A by restricting technology diffusion: $a_{12} < a_{13}$
- Player C loses if A retaliates (at virtually no cost to A) by restricting diffusion of its technology and increasing its emissions: $c_{12} < c_{13}$

So, restricting technology diffusion is a real threat, but not a credible one. If the stock of knowledge of player C increases in size relative to that of player A, the realness of the threat increases and its incredibility decreases.

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

The main question, however, is whether $a_{13} < a_{11}$, that is, is the threat of restricting technology diffusion effective? At first sight, the size argument does not apply here. If player A is small compared to player C, then the exclusion from C's technology will hit relatively hard. However, if A is small compared to C, then the benefits of defecting are relatively large. The ambiguity remains. However, $(a_{12}-a_{11}) < (a_{13}-a_{11})$, so that the incentive to defect is unambiguously smaller with potentially restricted technology diffusion than without. The crucial element is whether or not player C exercises its threat. To maintain its stability, it may want to do so, although it hurts. As it hurts less with small defectors, the threat of restricting technology diffusion is more effective for a relatively large coalition and a relatively small defector than for a relatively small coalition and a relatively large defector. We return to this issue in Section 5.

4. Alternative formulations

4.1. Investments in R&D

Technology can also be developed by investing in R&D. Returning to the case with one player, the objective function (1) becomes:

(28) $$\min_{R_t, I_t} \sum_{t=0}^{\infty} \frac{f_t(R_t, H_t) + g_t(S_t) + h_t(I_t)}{(1+\rho)^t}$$

with

(29) $$h_t(I_t) = k_t I_t^2$$

(30) $$H_t = \gamma H_{t-1}\sqrt{1+I_{t-1}} = \gamma^t H_0 \prod_{s=1}^{t} \sqrt{1+I_{t-s}}$$

and the other equations unchanged. *I* denotes investments in R&D.

The first-order conditions for this problem are:

(31) $$\frac{2k_t I_t}{(1+\rho)^t} - \sum_{s=1}^{\infty} \frac{\alpha_{t+s} R_{t+s}^2}{2H_{t+s}(1+\rho)^{t+s}(1+I_t)} = 0$$

and

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

Although this alternative specification has profound implications for the characteristics of the optimal greenhouse gas emission reduction trajectory, the effect of restricted technology diffusion on coalition formation is unaltered.

4.2. Secondary benefits

Greenhouse gas emission reduction is not only good for climate change. Other air pollutants are emitted as well by the same processes emitting greenhouse gases. Also, technological progress is not only good for cheaper emission abatement. Other benefits include economic growth, particularly in countries constrained by capital or energy supply. Such secondary benefits are readily included in the framework. Assuming these benefits to be strictly private, objective function (9) is replaced by:

(31) $$\min_{R_{t,r}} \sum_{t=0}^{\infty} \frac{f_{t,r}(R_{t\,r}, H_{t,r}) + g_{t,r}(S_{t,r}) - k_{t,r}(H_{t,r})}{(1+\rho_r)^t}$$

with *k* some positive and increasing function of knowledge stock *H*. Obviously, this increases optimal emission reduction. Equally obviously, if technology diffusion can be confined within the coalition, the incentive to co-operate increase. An alternative to equation (31), with similar properties is:

$$(32) \qquad \min_{R_{t,r}} \sum_{t=0}^{\infty} \frac{f_{t,r}(R_{t,r}) + g_{t,r}(S_{t,r}) - k_{t,r}(R_{t,r})}{(1+\boldsymbol{r}_r)^t}$$

In this formulation, the secondary benefits are due to the emission reduction. For example, greenhouse gas emission reduction may reduce conventional air pollution. We return to this formulation in Section 5.

5. Numerical analysis

Above, a number of ambiguities appear. This section explores the most important one, namely whether restricted technology transfer hurts a small region more than it gains by free-riding. To that end, a series of numerical analyses is reported.

The model is the same as in Section 2. Selected parameters are given in Table 1. The parameters reflect the broad consensus in the literature on the economics of climate change – see Hourcade *et al.* (1996), Nordhaus (1994) and Pearce *et al.* (1996). For simplicity, we only consider two players. One player is a large coalition of co-operative players. The second player is a small singleton considering a possible defection from the grand coalition. This is a (n-1) versus 1 game. This situation is found to be the most interesting case in Section 3.

For convenience, we assume $\boldsymbol{b}_{t,r} = \boldsymbol{b}_r \forall t$ – cf. Equation (17) – and $\boldsymbol{w}_{t,r} = \boldsymbol{w}_r \forall t$ – cf. Equation (14-26). Emissions at time t follow from $E_{t,r}=E_{0,r}(1+g_t)^t$ with $g_t=0.01\ 0.995^t$. There is no autonomous technological progress: ã=1 – cf. Equation (14-26). The stock of atmospheric carbon is degraded at rate ä=0.0833 – cf. Equation (16) and Nordhaus (1994).

	á[a]	â[b]	ù[c]	ë[d]	E_0[e]	ñ[f]	Weight[g]	gain[h]
Base case	2	.02	.45	0	2	.03	10	
	2	.02	.06	0	.2	.03	1	.0010
Low cost	2							
	1							.0010
High cost	2		.					
	3							.0010
Low impact		.02						
		.01						.0002
High impact		.02						
		.03						.0023
Small learning			.45					
			.03					.0011
Large learning			.45					
			.09					.0009
Low Emissions					2			
					.1			.0008
High Emissions					2			
					.3			.0011
Low discount						.02		
						.02		.0019
High discount						.04		
						.04		.0005
Low weight							15	
							1	.0004
High weight							5	
							1	.0043
Maximum	2	.02	.45	0	2	.02	5	
	3	.03	.03	0	.3	.02	1	.0323
Low sec. ben.				.001				
				.001				.0692
Base sec. ben.				.001				
				.002				.1696
High sec. ben.				.001				
				.003				.5736

[a] Costs of emission reduction as a fraction of income – cf. Equation (13-25) – note that the costs depend on the fraction emission reduction squared.
[b] Impact of climate change as a fraction of income – cf. Equation (17) – note that the impacts depend on the atmospheric stock of carbon dioxide relative to a doubling of this stock.
[c] Learning by doing – cf. Equation (14-26).
[d] Secondary benefits as a fraction of income – cf. Equation (33) – note that the benefits depend on the square root of the fraction emission reduction.
[e] Initial emissions.
[f] Discount rate – cf. Equation (12-21).
[g] Weight in co-operative game.
[h] Increase in net present cost due to restriction of technology diffusion.

The model is solved in GAMS. The code can be found in the Appendix. GAMS-MINOS has some difficulty with learning-by-doing and games. These difficulties are overcome in the following manner. First, the co-operative game is solved without learning-by-doing. This is a standard problem for GAMS, solved without difficulties. The optimal emission reduction path of this problem is used as starting value in a second iteration. In this iteration, learning-by-doing is introduced, but only one-third as strong in the model of Section 2. The solution to this is used as starting value in the third iteration, in which learning-by-doing has a two-third strength. This is used as the starting value for the actual optimisation of interest.[5]

The outcome of the co-operative game is used as starting value for the nonco-operative game. This is solved by keeping one player's emission reduction fixed whilst optimising the other player's emission reduction. This is iterated until convergence.

Table 1 displays the results. The crucial column is the last. It gives the additional costs of restricted technology diffusion of small player as a fraction of her free-riding gains. In all cases, the gains far outweigh the costs, by a factor 1000 in the base case. In the maximum case, the gains outweigh the costs by a factor of about 30.

Secondary benefits follow Equation (32), specifically

(33) $\quad k_{t,r}(R_{t,r}) = k_r(R_{t,r}) = l_r\sqrt{R_{t,r}}$

Table 1 gives the parameters and the results. With secondary benefits, a restriction of technology diffusion takes away a substantial part of the gains of free-riding, but not enough to fully off-set these gains, not even if the secondary benefits get unrealistically high (cf. Pearce *et al.*, 1996).

6. Conclusion and discussion

The above analysis shows that technology transfer can help (internally) stabilise a large coalition. This conclusion is largely independent of the functional specification of the model. The only requirements are a technology that interests all players, and the ability to prevent nonco-operative players from using that technology.

The first condition also demonstrates the limitations of using induced technological change to stabilise climate coalitions. Players are only interested in carbon-saving technology in as far as it can help reduce climate change. Players indifferent to climate change are equally indifferent to carbon-saving technologies.

The threat of excluding nonco-operative players from technology diffusion is real (that is, it hurts), and may be effective (that is, it may help to prevent defection from the coalition). However, the threat is never credible (that is, it hurts the coalition to exercise the threat). This incredibility decreases if the coalition increases in size relative to the potential defector.

The above analysis begs the question of implementation. Is it possible to set-up a pool of carbon-saving technologies from which co-operating countries can draw, but non-co-operating countries cannot, or at a substantially higher price?

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[5] The number of iterations and the step-size were found by trial and error.

The answer is maybe. The fact that the technology fund would contain technologies developed in a specific context, for a specific purpose implies that WTO-rules could be bent to make this arrangement a legal one. There are four caveats to this. Firstly, patents are routinely pirated. Secondly, not governments but companies hold the patents. Thirdly, the USA is both reluctant to reduce greenhouse gas emissions and a major developer of technology. Developing countries, which would gain most of emission abatement, have the least technology to offer. Fourthly, the threat of excluding defectors from the technology pool should be exercised automatically.

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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                     /0.00/
D2              secondary benefits player 2                     /0.00/
RHO             discount rate                                   /0.03/
DELTA           carbon uptake                                   /0.008/
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
HEQ0
```

```
HEQ1
HEQ2
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);
HEQ0(T+1)..     H(T+1) =E= H(T);
HEQ1(T+1)..     H(T+1) =E= H(T)*((1+0.33*R1(T))**C1)*((1+0.67*R2(T))**C2);
HEQ2(T+1)..     H(T+1) =E= H(T)*((1+0.67*R1(T))**C1)*((1+0.67*R2(T))**C2);
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 COOQ0 /HIN, HEQ0, SIN, SEQ, TC1FD, TC2FD, NPV1, NPV2, NPV/;

SOLVE COOQ0 MINIMIZING NPVC USING NLP;

SOLVE COOQ0 MINIMIZING NPVC USING NLP;

MODEL COOQ1 /HIN, HEQ1, SIN, SEQ, TC1FD, TC2FD, NPV1, NPV2, NPV/;

SOLVE COOQ1 MINIMIZING NPVC USING NLP;

SOLVE COOQ1 MINIMIZING NPVC USING NLP;

MODEL COOQ2 /HIN, HEQ2, SIN, SEQ, TC1FD, TC2FD, NPV1, NPV2, NPV/;

SOLVE COOQ2 MINIMIZING NPVC USING NLP;

SOLVE COOQ2 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;
```