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Abstract

Uncertainty and learning play an important role in addressing the problem of climate change. In stylized game-theoretic models of international environmental treaty formation, which capture the strategic interactions between nations, it has been shown that learning usually has a negative impact on the success of cooperation. This paper asks the question whether this negative conclusion carries over to an applied multi-regional climate model. This model captures the large heterogeneity between different world regions and considers not only uncertainty about the benefits but also about the costs from climate mitigation. By exploiting differences in costs and benefits between regions and allowing transfers to mitigate free-rider incentives, we derive much more positive conclusions about the role of learning.

JEL-Classification: D62, D80, Q54

Keywords: international climate agreements, uncertainty, learning, game theory, cost-benefit analysis

1. Introduction

Climate change is one of the greatest challenges to international co-operation the world is presently facing (Stern 2007 and IPCC 2007). Currently, a “Post-Kyoto” agreement is being negotiated that sets greenhouse gas emission targets for the period after 2012, the so-called “second commitment period”. One important element for the success of this new agreement is to ensure participation of all major polluters, including the USA, as well as the new emerging polluters China and India.

There are four key issues that make the climate change problem so difficult to solve: (i) the process of climate change is effectively *irreversible*; (ii) there are considerable *uncertainties* about the benefits and costs from mitigating climate change; (iii) our understanding of these uncertainties changes over time as a result of *learning* more about climate science and possible technological responses; (iv) the problem is *global*, but since there is no global authority that can enforce a climate treaty, *international environmental agreements* (IEAs) require voluntary participation.

The first three issues have been studied for instance by Kolstad (1996a, b), Ulph and Ulph (1997), Ulph and Maddison (1997) and Narain, Fisher and Hanemann (2007), though typically in the context of a single social planner. Depending on the model specification and assumptions, uncertainty either calls for laxer environmental standards today in order to benefit from more information about mitigation options in the future or calls for tougher standards in accordance with the precautionary principle, taking in consideration possibly high and irreversible environmental damages in the future. Short-term tighter environmental standards may also spur technological innovation, thus reducing future abatement costs, but may also cause lock-in effects if abatement options are associated with high fixed costs. In any case, in the context of a social planner, global welfare with learning is higher than without learning, as better informed decisions can be taken. We call this the *information effect* from learning.

There has also been an extensive literature, starting with Carraro and Siniscalco (1993) and Barrett (1994), followed by many others as surveyed for instance in Barrett (2003) and Finus (2003, 2008), on the fourth issue, though mainly in the context of perfect information. The conclusions have been rather pessimistic: while there are substantial benefits from cooperation, self-enforcing IEAs achieve only little.

Recently, several efforts have been made to combine these two strands of literature (Na and Shin 1998, Ulph 1998, Ulph 2004, Baker 2005, Ingham et al. 2007, Kolstad 2007, Dellink et al. 2008, Kolstad and Ulph 2008, 2009). Ulph (1998) demonstrates in a two-player-two-period model that in the Nash equilibrium, due to a negative *strategic effect* from learning as we call it, learning may lead to lower individual and global payoffs than no learning. Na and Shin (1998) confirm this negative conclusion about the role of learning in a stylized three-player model of coalition formation. By construction, and as in the model by Ulph (1998), players are ex-ante symmetric but learn to be asymmetric ex-post and hence to benefit unequally from an IEA. Due to what we label a negative *stability effect* from learning, learning leads to a smaller stable IEA and lower global welfare. The possibility of a negative effect from learning is also captured in the dynamic coalition formation model in Ulph (2004) who distinguishes the case of variable membership (membership may change over time) and fixed membership (membership is decided once and for all). He finds that in the case of fixed membership, as we assume in our analysis, the expected level and variance of damages determine whether learning has a positive effect on the size of stable coalitions and global welfare.

Kolstad (2007) and Kolstad and Ulph (2008, 2009) extend and systematize the role of uncertainty, learning and IEA formation of which we make use in this paper. In a two-stage coalition formation game in which countries choose their membership in the first stage and their abatement strategies in the second stage, they distinguish three cases. 1) Uncertainty is not resolved. This is the case of *no learning*. 2) Uncertainty is not resolved before the second stage. This corresponds to the case of *partial learning*. 3) Uncertainty is resolved before the first stage. This corresponds to the case of *full learning*. In the two cases with learning, learning is perfect in the sense that all players learn the values of all uncertain parameters and no uncertainty remains.[1] All three papers confirm in a stylized model the negative role of learning.

This negative conclusion is certainly intriguing as it suggests that in the strategic context of IEA formation learning is bad, questioning intensified research efforts in climate change in recent years as well as the dissemination of knowledge through international institutions like International Panel on Climate Change (IPCC). Hence, one may wonder whether this result holds generally or may be an artifact of the special construction of these models. For instance, all models exclusively concentrate on uncertainty about the benefits from climate mitigation, assume symmetry with respect to abatement costs (and often also with respect to the benefits from global abatement) and abstract from transfers that could mitigate asymmetries of the gains from cooperation among players. Moreover, in Ulph (2004), Kolstad (2007) and

1 Thererfore, the term "partial learning" may be confusing as it reflects the timing of learning, not the nature of learning, i.e. all information is revealed before stage 2. An alternative term could be "delayed learning". To ease comparison with the studies of Kolstad and Ulph, we adopt their terminology.

Kolstad and Ulph (2008, 2009) the payoff function is linear, implying binary equilibrium abatement strategies in the second stage of coalition formation: abate or not abate. In order to shed some light on this issue, we extend the model of Dellink et al. (2008), an applied climate-economy model with twelve world regions. Different from their analysis, we consider not only the case of no and full learning but also partial learning; we furthermore introduce transfers. From our numerical simulations, we derive much less negative conclusions: learning is always better than no learning (e.g. generates higher global welfare) and full learning is better than partial learning if accompanied by a transfer scheme, mitigating free-rider incentives in an optimal way.

In the following, we lay out the theoretical setting in Section 2, describe the applied model in Section 3 and report about our results in Section 4. Section 5 summarizes our main findings and draws some conclusions.

2. The Models of Coalition Formation and Learning

In order to relate the three models of uncertainty and learning (no learning, partial learning, full learning) to the standard model without uncertainty, we start by describing the deterministic setting. For the purpose of expositional simplicity, we abstract from time-dependencies in the payoff function in this section, and explain the dynamics in the context of our applied model in Section 3.

2.1 Certainty

Consider a set of N heterogeneous players, each representing a country or world region. Moreover, consider the following simple two-stage coalition formation game, frequently applied in the analysis of IEAs.[2] In the first stage, players decide whether

[2] For an overview see for instance Barrett (2003) and Finus (2003, 2008).

to become a member of an IEA or to remain an outsider. Announcement $c_i = 1$ means "player i joins the agreement" and announcement $c_i = 0$ "player i remains an outsider", i.e. remains a singleton (sometimes called a fringe player); a coalition structure c is then described by the announcement vector $c = (c_1, ..., c_N)$, $c \in C$. Players that announce 1 are called coalition members and this set is denoted by $k = \{i \mid c_i = 1, \forall\, i = 1,...,N\}$. Thus, in this simple setting, a coalition structure is entirely defined by coalition k. Hence, we can use the term coalition structure and coalition interchangeably. We denote the set of coalitions by K.

In the second stage, players choose their abatement levels. This leads to abatement vector $q = (q_1, ..., q_N)$. The payoff of an individual player i, $\pi_i(q, z_i)$ depends on abatement vector q, i.e. the strategies of all players, due to the public good nature of climate change, and on a vector of parameters z_i that enter the payoff function of player i.

The game is solved backward assuming that strategies in each stage must form a Nash equilibrium. For the second stage, this entails that abatement strategies form a coalitional Nash equilibrium between coalition k and the fringe players $j \notin k$:

$$\begin{array}{r} \sum_{i \in k} \pi_i(q_k^*, q_{-k}^*, z_i) \geq \sum_{i \in k} \pi_i(q_k, q_{-k}^*, z_i) \quad \forall q_k \quad \textit{and} \\ \forall j, c_j = 0: \; \pi_j(q_k^*, q_j^*, q_{-j}^*, z_j) \geq \pi_j(q_k^*, q_j, q_{-j}^*, z_j) \quad \forall q_j \end{array} \tag{1}$$

where q_k is the abatement vector of coalition k, q_{-k} the vector of all players not belonging to k, q_j abatement of fringe player j, and q_{-j} the vector of all other fringe players except j. An asterisk denotes equilibrium strategies.

Since in the context of our applied model the equilibrium abatement strategy vector q^* is unique for every coalition structure k and a given matrix of parameters $\boldsymbol{z}$, there is a unique vector of equilibrium payoffs for every coalition structure k (see the proof in Olieman and Hendrix 2006). These are called valuations: $v_i(k,\boldsymbol{z}) \equiv \pi_i(q^*(k,\boldsymbol{z}))$. Since coalition structure k follows from announcement vector c we may also write: $v_i(c,\boldsymbol{z}) \equiv \pi_i(q^*(c,\boldsymbol{z}))$.[3]

Also in the first stage, stability requires that strategies form a Nash equilibrium. That is, no member that announced $c_i = 1$ should have an incentive to change this announcement to $\tilde{c}_i = 0$ (internal stability) and no fringe player that announced $c_i = 0$ should want to announce $\tilde{c}_i = 1$ (external stability), given the announcement of other players c_{-i}. These conditions are compactly summarized by the stability function $s(c,\boldsymbol{z})$, which assigns the value 1 to a stable and the value 0 to an unstable announcement vector:

$$s(c,\boldsymbol{z}) = \begin{cases} 1 & if \ \forall\, i \in N, \tilde{c}_i = 1\text{-}c_i \ : v_i(c_i, c_{-i}, \boldsymbol{z}) - v_i(\tilde{c}_i, c_{-i}, \boldsymbol{z}) \geq 0 \\ 0 & else \end{cases} \tag{2}$$

where $\tilde{c}$ is constructed by changing the announcement of one player at a time. Note that the singleton coalition structure is stable by definition as it can be supported by an announcement vector where all players announce $c_i = 0$. Hence, single deviations make no difference. Consequently, existence of an equilibrium is guaranteed.

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3 We adopt the convention that equilibrium abatement strategies are derived from payoffs that depend on individual parameters whereas valuations, which depend on equilibrium strategies of all players depend on all parameters.

It is worth noting that for any given set of parameters $\boldsymbol{z}$, this function may imply multiple stable coalitions. We denote the set of Pareto-undominated stable coalitions by $\Sigma(\boldsymbol{z}) \subseteq C$ and the number of stable Pareto-undominated coalitions by $\#\Sigma(\boldsymbol{z})$. In order to measure the success of coalition formation, we compute the average aggregate valuation over all Pareto-undominated stable coalitions: $\bar{v}(\Sigma(\boldsymbol{z})) = \frac{\sum_{c \in C} s(c,\boldsymbol{z}) \sum_{i=1}^{N} v_i(c,\boldsymbol{z})}{\#\Sigma(\boldsymbol{z})}$, assuming that all Pareto-undominated stable coalitions are equally likely. In a similar spirit, we could compute other indicators of global performance like the average abatement or, as we do in our numerical simulations, the average concentration of CO_2 (see Sections 3 and 4).

Note finally that our assumption about the second stage abstracted from the possibility of transfers, i.e. $v_i(c,\boldsymbol{z}) \equiv \pi_i(q^*(c,\boldsymbol{z}))$. In the context of heterogeneous players this may imply quite different valuations and hence asymmetric gains from cooperation. This may hamper the formation of large stable coalitions and hence the success of cooperation as has been demonstrated for instance in Bosello et al. (2003) and Botteon and Carraro (1997). However, it has also been shown that the assumption about the particular transfer scheme can crucially affect the set of stable coalitions (Carraro et al. 2006). In order to avoid this sensitivity, we employ the concept of an almost ideal transfer scheme put forward by Eyckmans and Finus (2004), with a similar notion in Fuentes-Albero and Rubio (2005), McGinty (2007) and Weikard (2009). The idea builds on the observation that a coalition k derived from an announcement vector c is potentially internally stable ($s^{PI}(c,\boldsymbol{z}) = 1$) or potentially internally unstable ($s^{PI}(c,\boldsymbol{z}) = 0$) if and only if

$$s^{PI}(c,\mathbf{z})=\begin{cases}1 & if\ \ \forall\, i,\, c_i=1, \tilde{c}_i=1\text{-}c_i\ :\sum_{i\in k}\Big(v_i(c_i,c_{-i},\mathbf{z})-v_i(\tilde{c}_i,c_{-i},\mathbf{z})\Big)\geq 0\\ 0 & else\end{cases} \tag{3}$$

In other words, if and only if $s^{PI}(c,\mathbf{z})=1$ there exists a transfer scheme that makes announcement vector c internally stable. As shown in Eyckmans and Finus (2004), a sharing scheme addressing potential internal stability gives every coalition member its free-rider payoff when leaving the coalition, $v_i(\tilde{c}_i,c_{-i},\mathbf{z})$, plus an (arbitrary) share λ_i of the surplus which is the aggregate payoff of the coalition minus the sum of free-rider payoffs:

$$\begin{aligned}&\forall\, i,\, c_i=1: v_i^T(c_i,c_{-i},\mathbf{z})=v_i(\tilde{c}_i,c_{-i},\mathbf{z})+\lambda_i\left[\sum_{i\in k}\Big(v_i(c_i,c_{-i},\mathbf{z})-v_i(\tilde{c}_i,c_{-i},\mathbf{z})\Big)\right]\\ &\forall\, j,\, c_j=0: v_j^T(c_j,c_{-j},\mathbf{z})=v_j(c_j,c_{-j},\mathbf{z})\\ &\sum_{i\in k}\lambda_i=1\end{aligned} \tag{4}$$

where the superscript T implies valuations after transfers. This means that transfers are only paid among coalition members, these transfers balance, i.e. there are no external sources of transfers. This sharing scheme has some interesting properties: all transfer systems belonging to this scheme, irrespective of the set of shares, leads not only to the same set of internally stable coalitions but also externally stable coalitions and hence stable coalitions (robustness). This is because a coalition k is only externally stable if and only if all coalitions $k\cup j$ for all $j\notin k$ are not potentially internally stable and hence not internally stable. Moreover, this transfer scheme stabilizes those coalitions that generate the highest aggregate welfare among those coalitions that can be stabilized at all (optimality), which may not be possible for some larger coalitions due to too strong free-rider incentives. This also means that an expansion of stable coalitions through transfers from insiders to outsiders is not feasible (Carraro et al. 2006). In other words, this transfer scheme exhausts all possibilities of cooperation.

For practical purposes of determining stable coalitions, we only have to replace $v_i(c,\boldsymbol{z})$ in (2) by $v_i^T(c,\boldsymbol{z})$, assuming the transfer scheme in (4).

2.2 Uncertainty

In a stochastic model, the matrix of deterministic parameters $\boldsymbol{z}$ is replaced by the stochastic matrix $\boldsymbol{Z}$ with distribution $f\left(z_{i,u}\right)$ for a particular parameter $z_{i,u}$ in player i's payoff function, $z_{i,u} \in \left(\underline{z_{i,u}}, \overline{z_{i,u}}\right)$,[4] $u \in \{1,...,\ell\}$, where the payoff function of all players comprises the same number of parameters ℓ. We assume that this distribution is common knowledge.

2.2.1 No Learning

In the case of *N*o *L*earning, in the second stage, the true parameter values are not revealed and thus expected payoffs have to be maximized. Thus, equilibrium condition (1) is replaced by

$$\begin{aligned} &\textstyle\sum_{i\in k} E\left[\pi_i(q_k^*,q_{-k}^*,Z_i)\right] \geq \textstyle\sum_{i\in k} E\left[\pi_i(q_k,q_{-k}^*,Z_i)\right] \quad \forall q_k \quad \textit{and} \\ &\forall j, c_j = 0:\ E\left[\pi_j(q_k^*,q_j^*,q_{-j}^*,Z_j)\right] \geq E\left[\pi_j(q_k^*,q_j,q_{-j}^*,Z_j)\right] \quad \forall q_j \end{aligned} \tag{5}$$

where $E\left[\pi_i(\cdot,\cdot,Z_i)\right] = \int_{\underline{z_{i,1}}}^{\overline{z_{i,1}}} ... \int_{\underline{z_{i,\ell}}}^{\overline{z_{i,\ell}}} \pi_i(\cdot,\cdot,z_i) f\left(z_{i,1},...,z_{i,\ell}\right) dz_{i,1}...dz_{i,\ell}$. Since in our applied model payoffs are linear in parameters (but not in abatement levels), certainty

4 These bounds can be minus and plus infinity, e.g. in the case of a normal distribution.

equivalence holds (see Dellink et al. 2008), i.e. $E\left[\pi_i(\cdot,\cdot,Z_i)\right] = \pi_i(\cdot,\cdot,E(Z_i))$ - the expected payoff is equal to the payoff with expected parameter vector $E(Z_i)$. We denote the equilibrium abatement vector satisfying the inequality system (5) by $q^{NL*}(c)$ and derive (expected) valuations $v_i^{NL}(c,E[\boldsymbol{Z}]) \equiv \pi_i^{NL}(q^{NL*}(c,E[\boldsymbol{Z}])$. Again, we may distinguish a case without and with transfers, as mentioned for the deterministic setting above.

In the first stage, stability with definition (2), replacing valuations in the deterministic setting by expected valuations: $s^{NL}(c,\boldsymbol{Z}) = 1$ iff $\forall i: v_i^{NL}(c,E(\boldsymbol{Z})) \geq v_i^{NL}(\tilde{c},E(\boldsymbol{Z}))$, 0 else.

As in the deterministic setting, we can compute an indicator of global performance: $\bar{v}^{NL} = \bar{v}(\Sigma^{NL}(\boldsymbol{Z})) = \dfrac{\sum_{c \in C} s^{NL}(c,\boldsymbol{Z}) \sum_{i=1}^{N} v_i^{NL}(c,E(\boldsymbol{Z}))}{\# \Sigma^{NL}(\boldsymbol{Z})}$, which is the average expected aggregate valuation over all Pareto-undominated stable coalitions.

2.2.2 Partial Learning

In the case of *P*artial *L*earning, in the second stage, before players choose their abatement strategies, they learn the value of the stochastic matrix $\boldsymbol{Z}$. Hence, they make the correct abatement decision based on realization z of $\boldsymbol{Z}$: $v_i(c,z_i) \equiv \pi_i(q^*(c,z_i))$ where again the case without and with transfers may be distinguished. Since players have to decide upon their membership under uncertainty, they will base their decision in the first stage on expected valuations: $v_i^{PL}(c,z_i) = E(v_i(c,\boldsymbol{Z})) = \int_{\underline{z_{i,1}}}^{\overline{z_{i,1}}} \dots \int_{\underline{z_{i,\ell}}}^{\overline{z_{i,\ell}}} v_i(c,\boldsymbol{z}) f\left(z_{i,1},\dots,z_{i,\ell}\right) dz_{i,1} \dots dz_{i,\ell}$. Hence, in order to determine stable coalitions with the stability function defined in (2), we only have to replace the valuation by the expected valuation as in the case of no learning (though both expected values are different!): $s^{PL}(c,\boldsymbol{Z})=1$ iff $\forall i: v_i^{PL}(c) \geq v_i^{PL}(\tilde{c})$, 0 else. We compute the associated indicator of global performance:

$$\bar{v}^{PL} = \bar{v}(\Sigma^{PL}(\boldsymbol{Z})) = \frac{\sum_{c \in C} s^{PL}(c,\boldsymbol{Z}) \sum_{i=1}^{N} v_i^{PL}(c))}{\# \Sigma^{PL}(\boldsymbol{Z})}.$$

2.2.3 Full Learning

In the case of *F*ull *L*earning, players know even before the first stage the realization of the stochastic matrix $\boldsymbol{Z}$. Hence, analogously to the deterministic setting, for realization *z*: $s^{FL}(c,z_i)=1$ iff $\forall i: v_i^{FL}(c,z_i) \geq v_i^{FL}(\tilde{c},z_i)$, 0 else, with $v_i^{FL}(c,z_i) \equiv v_i(c,z_i) \equiv \pi_i(q^*(c,z_i))$.

From an ex-ante perspective, we can assign a *S*tability *L*ikelihood (SL) that coalition c is stable which is $SL(c) = \int_{\underline{z_{1,1}}}^{\overline{z_{1,1}}} \ldots \int_{\underline{z_{N,\ell}}}^{\overline{z_{N,\ell}}} s(c,\boldsymbol{z}) f\left(z_{1,1},\ldots,z_{N,\ell}\right) dz_{1,1} \ldots dz_{N,\ell}$.[5] Average expected aggregate valuations over all Pareto-undominated stable coalitions and all possible realizations of $\boldsymbol{Z}$, which is our indicator of global performance, is computed as

$$\bar{v}^{FL} = \bar{v}(\Sigma^{FL}(\boldsymbol{Z})) = \int_{\underline{z_{1,1}}}^{\overline{z_{1,1}}} \ldots \int_{\underline{z_{N,\ell}}}^{\overline{z_{N,\ell}}} \frac{\sum_{c \in C} s^{FL}(c,\boldsymbol{z}) \sum_{i=1}^{N} v_i^{NL}(c,\boldsymbol{z}))}{\# \Sigma^{FL}(\boldsymbol{z})} f\left(z_{1,1},\ldots,z_{N,\ell}\right) dz_{1,1} \ldots dz_{N,\ell}.$$

2.2.4 Relating the Three Models of Learning

Partial and full learning are identical in the second stage. Hence, when abstracting from the stability of coalitions related to the first stage, for every coalition $k \in K$

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5 This is called expected membership in Kolstad and Ulph (2009).

derived from some announcement vector $c \in C$, these two models of learning lead to the same outcome in the second stage.

Turning to the first stage, all three models of learning are different. Though membership decision under no and partial learning are based on expected valuations, they will usually differ. In the case of no learning, expected payoffs are derived from maximizing expected payoffs from which an expected abatement vector is derived. In the case of partial learning, players derive an equilibrium abatement vector for all possible realizations of parameters and then derive expected payoffs by taking expectations over all possible realizations of parameters. Finally, under full learning both membership and abatement decisions are based on realizations.

Consequently, under no and partial learning a coalition is either stable or not stable whereas under full learning stability depends on the realization of the parameters and we calculate a stability likelihood. In order to evaluate the three models of learning, we compute the expected aggregate payoff over all players and all Pareto-undominated stable coalitions.

A priori little can be predicted about the relation between the three models of learning in terms of the final outcome (measured by the indicators of global performance) because of the interplay of the three effects mentioned in the introduction (information effect, strategic effect and stability effect). General statements are only possible for very restrictive assumptions on the functional form of the payoff functions and the uncertainty of the parameters (see, e.g. Yi and Shin 1998, Kolstad 2007 and Kolstad and Ulph 2008, 2009). Therefore, we turn to an evaluation based on numerical simulations using an applied climate model which we lay out in the next section.

3. The Applied Climate Model

The applied climate model, called *Sta*bility of *Co*alitions model (STACO), builds upon the model as presented in Dellink et al. (2008), with a number of extensions inspired by Nagashima et al. (2009). We focus only on the main characteristics of the model; for a detailed description see Dellink et al. (2008) and Nagashima et al. (2009). The core of the model consists of a payoff function that represents the net present value of a stream of benefits and costs arising from abatement activities. In contrast to Dellink et al. (2008), abatement is not constant but may vary over time. The payoff of an individual player i depends on the abatement matrix $\boldsymbol{Q}$ of dimension $N \times T$ and on the vector of parameters Z_i of length ℓ with Z_{iB} those parameters relating to the benefit function $B_{it}(\bullet)$ and Z_{iC} those relating to the cost function $C_{it}(\bullet)$:

$$\pi_i(\boldsymbol{Q}, Z_i) = \sum_{t=1}^{T}\Big((1+r)^{-t} \cdot (B_{it}(q_t; Z_{iB}) - C_{it}(q_{it}; Z_{iC}))\Big) \qquad (6)$$

where the planning horizon is T, t is the index for time and r is the discount rate. Abatement costs depend on individual abatement q_{it} and benefits depend on aggregate abatement $q_t = \sum_{i=1}^{N} q_{it}$, reflecting the public good nature of climate change. Hence, $\pi_i(\boldsymbol{Q}, Z_i)$ is the net present value of player i of the stream of benefits and costs accruing from own abatement but also from all other players over the entire time horizon. We compute the equilibrium abatement path for each possible coalition structure which upon substitution in the payoff function delivers discounted valuations. They are the basis for taking membership decision and hence we assume fixed membership over the time horizon T.[6] The time horizon is 100 years, ranging from 2011 to 2110.

We consider twelve world regions; USA (USA), Japan (JPN), European Union - 15 (EU15), other OECD countries (OOE), Eastern European countries (EET), former Soviet Union (FSU), energy exporting countries (EEX), China (CHN), India (IND), dynamic Asian economies (DAE), Brazil (BRA) and rest of the world (ROW). Following Nagashima et al. (2009), we assume an exogenous rate of technological progress which reduces abatement costs by 0.5% per annum and a discount rate of 2%; both are not subject to uncertainty. The functional form of the benefit and cost functions of all regions, including the assumptions about the structural parameters (mean, standard deviation and distribution) are summarized in the Appendix and discussed in Dellink et al. (2008). Here, we only briefly discuss some general features.

The benefit function is a linear approximation of a three-layer carbon cycle proposed by Nordhaus (1994) and links current global abatement activities to a stream of future avoided damages. The distribution of the global benefit parameter is given by a two-sided exponential function proposed by Tol (2005) with a mean value of 77 US$/ton. The mean values of the regional benefit shares are taken from Finus et al. (2006). Due to the large uncertainties associated with these shares, two sets are considered which are called Calibration I and II. For the distribution of regional shares we assume in accordance with Dellink et al. (2008) a right-skewed gamma distribution function that ensures positive regional shares. Abatement costs are given by a cubic function based

6 Fixed membership is a simplifying assumption, though widespread in the literature (e.g. Bosello et al. 2003 and Eyckmans and Finus 2006) due to conceptual and computational complexities. Flexible membership has only be considered in the stylized models with symmetric players in Ulph (2004) and Rubio and Ulph (2007).

on Ellerman and Decaux (1998). The stochasticity of this function is driven by a scaling parameter with a normal distribution, i.e. the cubic and quadratic term in the abatement cost function move together (cf. Dellink et al., 2008). Standard deviations of the benefit and abatement cost functions reflect a larger uncertainty about regions' benefit than cost parameters and a larger uncertainty about the parameters of non-OECD than of OECD regions.

Undoubtedly, all assumptions are simplifications and some have to be based on "guesstimates" (especially with respect to the benefits of abatement) as no better information is currently available. Hence, the absolute numbers presented below should be interpreted with caution. Nonetheless, our calibration provides a good indication of the relative position of the major world regions. Furthermore, we explicit take account of this principal uncertainty by considering five calibration scenarios. Compared to the Base Scenario, scenarios 2 to 5 can be viewed as a sequence of sensitivity analyses in which only one assumption is modified at a time.

1) The Base Scenario assumes the parameter values as described above and in the Appendix. This implies in particular a discount rate of 2 %, regional benefit shares under Calibration I and associated standard deviations as listed in Table A2 in the Appendix.

2) The Lower Discount Rate Scenario assumes a discount rate of only 1% (as opposed to 2% in the Base Scenario) which reflects a pure rate of time preference of virtually zero (cf. Stern, 2007).

3) The Higher Discount Rate Scenario assumes a higher discount rate of 3% (as opposed to 2% in the Base Scenario), reflecting a higher pure rate of time preference.

4) The Higher Variance of Regional Benefits Scenario assumes a standard deviation of regional benefit parameters twice as large as in the Base Scenario (and as listed in Table A2 in the Appendix), reflecting that the uncertainties in projected damage levels are not well-known, especially on a regional scale.

5) The Different Regional Benefit Shares Scenario assumes alternative mean values of regional benefit shares as proposed in Finus et al. (2006) to which we refer as Calibration II in Table A2 in the Appendix.[7] The mean shares in the Base Scenario (Calibration I) are relatively large for the OECD regions, due to their high GDP levels. In this alternative scenario (Calibration II), larger weights are given to damages in developing regions, especially India and Rest-of-the-World.

Computations are undertaken with Monte Carlo Simulations, drawing 20,000 samples from the stochastic model parameters. Equilibrium abatement levels, payoffs, transfers, valuations and stable coalitions for the three models of learning are computed as described in Section 2.

4. Results

4.1 General Remarks

Tables 1 to 5 show the results for the three models of learning for the five calibration scenarios described in Section 3. It is worthwhile pointing out that the reported global welfare and final-period concentration levels are expected values, though we may not mention this explicitly in the following. Moreover, one statement of caution is in order: though the best-performing coalitions (BPSC) in the no and partial learning model can be compared, they cannot be directly related to the coalition with the

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7 Standard deviations are also adjusted in this scenario such that the ratio between standard deviation and mean values are the same as in the Base Scenario.

highest stability likelihood (HSLC) in the full learning model. In the former case, the largest global welfare level defines "best-performing", whereas in the latter case the highest stability likelihood is the criterion for selection – other coalitions with a lower SL may generate higher global welfare levels but are less likely to arise. However, a direct comparison is possible for the indicators of global performance, which reflect averages over all stable coalitions. Apart from these general statements, the following remarks apply.

{Insert Tables 1-5 around here}

First, the Nash equilibrium as well as the social optimum coincide for partial and full learning in all tables because abatement decisions in the second stage are the same for each possible coalition structure.

Second, the smaller the discount rate, the higher are discounted global welfare levels and the lower are final-period concentration levels in the Nash equilibrium and in the social optimum (see Tables 1 to 3). This simply follows from the fact that a lower discount rate gives more weight to the long-term future benefits from reduced greenhouse emissions compared to current abatement costs. The discount rate also matters for the potential gains from cooperation: the difference between Nash equilibrium and social optimum in terms of global welfare and concentration levels is larger for lower discount rates. As a rule of thumb, in our applied model, global welfare in the social optimum in all three models of learning is three times larger than in the Nash equilibrium. Due to the existence of a non-zero concentrations level in 2010 and a small natural removal rate of greenhouse gases over time, the difference is less pronounced in terms of concentrations: on average concentrations in 2110 are 15% lower in the social optimum than in the Nash equilibrium.[8]

Third, in the no learning model optimal abatement strategies do not depend on the variance of regional benefit shares as they are based on expected parameter values. Hence, all entries under no learning in Tables 1 and 4 are the same. In contrast, it is interesting to observe for the models of full and partial learning that a higher variance of regional benefits shares in Table 4 increases the gap between Nash equilibrium and social optimum compared to Table 1. The intuition is that the potential gains from cooperation increase with the degree of diversity between regions. Whether and under which conditions such gains can be reaped through stable agreements will be analyzed in section 4.3 below.

Fourth, in the social optimum regional benefit shares do not matter for optimal abatement strategies as the first order conditions require that each region sets discounted marginal abatement cost equal to the discounted sum of marginal benefits. Hence, the results for the social optimum in Tables 1 (Base Scenario) and 5 (Different Regional Benefit Shares Scenario) are the same for each model of learning.

Fifth, in terms of the number and members of stable coalitions, outcomes are relatively robust for four (Tables 1 to 4) of the five calibration scenarios. For all three models of learning, main differences occur for different regional benefit shares (Table 5) as they crucially determine the distribution of gains from cooperation. For no and partial learning without transfers there is a unique non-trivial coalition (which Pareto-dominates the trivial coalition) for all five calibration scenarios. With transfers, the

8 Note that concentration levels in the Nash equilibrium are already lower than in Business-as-usual, as some abatement is undertaken by regions. The numbers have to be viewed as an approximation as our model does not contain a full climate module.

number of stable coalitions is much larger (e.g. 105 for no learning and 41 for partial learning in the Base Scenario, Table 1), in line with the results from deterministic models (e.g. Carraro et al. 2006, Eyckmans and Finus 2006 and Nagashima et al. 2009). For full learning, stability likelihood is always below 30% (e.g. 23.7% without and 15.9% with transfers in the Base Scenario, Table 1).

4.2 Comparing the Three Models of Learning: Abstracting from Stability

In order to analyze how the three effects described in the introduction (information, strategic and stability effect) influence the outcome in the three models of learning, we abstract from stability in a first step. This allows us to isolate the information and strategic effect from the stability effect. This implies that we only look at the second stage of coalition formation.

Result 1: Global Welfare and Concentration Abstracting from Stability

In each calibration scenario, and in every coalition structure, the following ranking with respect to global welfare levels and concentration levels applies for the three models of learning:

Global Welfare: FL=PL>NL *Concentration: FL=PL>NL.*

First note that Result 1 can be seen in Tables 1 to 5 only in terms of the social optimum, corresponding to the grand coalition, and the Nash equilibrium, corresponding to the singleton coalition structure. The statement that this ranking applies to all 4084 possible coalition structures derives from additional computations which are available upon request.

Second, consider the social optimum. Since all regions form the grand coalition, only the information effect matters. In qualitative terms, this effect implies that global welfare for partial and full learning is higher than for no learning as predicted by theory. In quantitative terms, it is interesting that this difference is substantial in our applied model.[9] Taking the average over the five calibration scenarios global welfare in the social optimum is almost 50% higher with learning than without learning. In contrast, for concentrations this relation is reversed, suggesting that regions on average abate more without learning. The average over the five calibration scenarios gives a 3.5% lower concentration level in 2110 for no learning than learning in the social optimum. The intuition is that under no learning regions choose abatement only on average correctly, which leads to overshooting on average compared to learning where they always get it "right".[10] The policy relevance of this result is that the conventional wisdom may be wrong that more information leads to better outcomes. In our applied model, this is true in terms of payoffs, but not in terms environmental effectiveness.

Third, consider the Nash equilibrium. Now the strategic effect comes into play which is particularly pronounced because all players behave non-cooperatively. Again, global concentration levels are higher with than without learning (1% as an average over the five calibration scenarios), and this is also true for global welfare (37% as an average over the five calibration scenarios). As the strategic effect works in the opposite direction of the information effect, we can conclude that, in our model, the information effect dominates the strategic effect, leading to higher global welfare but also higher concentration with than without learning. In our model, this applies not

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9 In the theoretical models of Kolstad (2007) and Kolstad and Ulph (2008, 2009) the information and the strategic effects are zero.

10 Due to the complexity of our model with heterogeneous players and uncertainty about the benefit and cost parameters, we cannot analytically prove the ranking FL=PL>NL for concentrations, neither for the social optimum nor for any other coalition structure. Already Ulph (1998) pointed out that no general results with respect to abatement are available for the Nash equilibrium and social optimum in two period models.

only to the Nash equilibrium with no cooperation but also to all non-trivial coalition structures of partial cooperation.

Result 2: Regional Welfare Abstracting from Stability

In each calibration scenario, and in every coalition structure, the following ranking with respect to regional welfare levels applies for the three models of learning:

Non-members without and with transfers: *FL=PL>NL*

Members without transfers: *FL=PL*

Members with transfers: *FL=PL>NL.*

Result 2 is interesting as a preparation for our stability analysis in section 4.3 and draws again on the computations for all possible coalition structures (not displayed in Tables 1 to 5 but available upon request). It illustrates our claim that analytical predictions about the outcome in the three models of learning are difficult. First, non-members' payoffs are always higher with learning.[11] Since this is not necessarily true for members in the setting without transfers, it may well be that this results in smaller coalitions for learning. Second, even though with transfers all players are better off with learning, both the incentive to stay in a coalition and the incentive to stay outside the coalition increase. Hence, predictions of what this implies for stability are not straightforward.

[11] One would expect that non-members are better off under no learning than under learning as they benefit from lower concentration levels (cf. Result 1). This is certainly true and hence the strategic effect from learning is negative for non-members. However, it appears that in our model the positive information effect from learning is stronger.

4.3 Comparing the Three Models of Learning: Including Stability

We now include the first stage of coalition formation in our analysis of overall success of coalition formation (i.e. Global Performance in Tables 1 to 5) for the three models of learning.

Result 3: Global Performance Including Stability

In each calibration scenario, the following ranking applies:

Expected Global Welfare
No Transfers: PL>FL>NL *Transfers: FL>PL>NL*

Expected Concentration
No Transfers: FL>PL>NL *Transfers: PL>FL, NL>FL.*

Result 3 suggests that in terms of global welfare both models of learning perform better than no learning, only the ranking of partial and full learning is reversed for transfers. This is in sharp contrast to the findings in stylized models that "learning is bad". Na and Shin (1998) find NL>FL and Kolstad (2007) and Kolstad and Ulph (2009, 2009) find NL>FL>PL in most cases and in a very few cases PL>NL>FL. Though they do no consider transfers, even without transfers our results are just the opposite.

One reason for this difference that applies to all these models is that they consider only uncertainty about the benefits from abatement whereas we consider also uncertainty about the abatement costs. In particular, in Na and Shin (1998) regional benefits are assumed to be negatively correlated but ex-ante all players expect the same benefits. Thus, learning without transfers leads to asymmetric gains from cooperation in their model, upsetting large stable coalitions with learning. In contrast, in our model, regional benefit shares are not correlated, expectations are not identical without learning, possible asymmetries on the benefit side may be compensated (or aggravated) by asymmetries on the cost side and finally, asymmetries can be mitigated through transfers.

Another reason for this difference relates to the linear payoff function in Kolstad (2007) and Kolstad and Ulph (2009) implying very different driving forces. In their model the equilibrium abatement choice is binary: abate or not abate. Consequently, what we call the information and strategic effects do not exist in their model. Moreover, in their model, stable coalitions can only be a knife-edge equilibrium: once a coalition member leaves, the coalition breaks apart as for the remaining coalition members it no longer pays to abate. This causes a positive effect from learning in terms of the size of stable coalitions but has a negative effect on global welfare. Clearly, in our model, a larger coalition size would always produce higher welfare if no other effects are at work.

Result 3 also suggests that what has already been observed abstracting from stability considerations also holds when including stability, at least without transfers: both models of learning lead to higher concentration levels. With transfers this is different. In particular full learning benefits from transfers which make it possible to stabilize much larger coalitions. This translates not only into higher expected welfare but also into higher expected abatement and thus lower expected concentration levels. The ranking of partial and no learning depends on the calibration scenario. For the Base Scenario, partial learning implies higher concentrations, both without and with transfers, but this may be reversed for other scenarios.

Result 4: Global Performance Including Stability: The Role of Transfers

In each calibration scenario, and in each model of learning, expected global welfare levels are higher and expected concentration levels are lower with transfers than without transfers.

Let the relative gain from cooperation be measured by the difference between stable IEAs and the Nash equilibrium over the difference between the social optimum and the Nash equilibrium. The average relative gains from forming IEAs in the five calibration scenarios are given by:

Global Welfare:

No Transfers: NL: 2.67%, PL: 3.97%, FL: 1.2%

Transfers: NL: 26.31%, PL: 38.73%, FL: 63.29%

Concentration:

No Transfers: NL: 2.11%, PL: 2.80%, FL: 1.30%

Transfers: NL: 18.41%, PL: 29.29%, FL: 46.73%.

Hence, without transfers, the relative gains from stable cooperation are rather small for all three models of learning, regardless whether this is measured in terms of global welfare or concentration levels. Apart from the omnipresent free-rider incentives well-known from the literature (e.g. Carraro and Siniscalco 1993 and Barrett 1994), one reason is that the gains from cooperation are unequally distributed as regions are quite heterogeneous in terms of benefits and abatement cost in our applied model. The almost ideal transfer scheme mitigates these differences in an optimal way (e.g. Eyckmans and Finus 2006), taking account of the regional incentive structure. This drastically increases the success of coalition formation for all three models of learning, but this is no guarantee that the social optimum is obtained. The improvement through transfers is particular pronounced for the model of full learning.

Roughly speaking, without transfers, the expected payoffs under no and partial learning are on average more symmetric than the "true" payoffs under full learning on which membership decisions are based in the first stage. This hampers the formation of large coalitions under full learning. However, once transfers are introduced, the benefits from full learning can be fully reaped. A similar driving force underlies also the next result.

Result 5: Global Performance Including Stability: The Role of Diversity

A higher variance of regional benefits in a setting without transfers (with transfers) implies lower (higher) expected global welfare levels and higher (lower) expected concentration levels for the two models of learning.

Result 5 compares Tables 1 and 4. As pointed out above, the variance of regional benefits does not matter for no learning as longs as the expected parameter value remains the same. For the models of full and partial learning, a higher variance of regional benefits translates also into a higher variance in payoffs among members and ceteris paribus increases the heterogeneity among regions. Without transfers, this poses an obstacle to form large stable coalitions as it implies a more asymmetric distribution of the gains from cooperation. With transfers, this obstacle is removed and diversity is now an asset. Not only does the coalition benefit from internalizing the externality among its members but also from a cost-effective allocation of abatement duties. The larger the asymmetry, the more pronounced is the difference between the cost-effective coalitional and cost-ineffective Nash abatement levels and hence the larger are the gains from cooperation. This finding is in line with McGinty (2007) and Weikard (2009) who show that with transfers coalition formation may be more successful if players are more heterogeneous.

5. Summary and Conclusion

In stylized models, which capture the strategic aspects of self-enforcing climate treaty formation, it has been shown that learning has a negative impact on the success of cooperation. This result is intriguing and runs counter to all intensified research efforts in climate change in recent years, aiming at reducing uncertainty about the impacts of climate change and the costs involved in mitigation. In this paper, we pose the question whether the negative conclusion about the role of learning holds more generally if the restrictive assumptions of the stylized models are relaxed. We use a calibrated climate change model with twelve world regions, which captures the dynamics of greenhouse gas accummulation in the atmosphere, the timing when the benefits and costs from climate mitigation occur and the large heterogeneity across regions, to address this question. The distribution of the uncertain parameters of the benefit and cost functions are generated through a Monte Carlo Simulation technique. The large uncertainties still surrounding these uncertain parameters is accounted for through sensitivity analyses. Three models of learning are investigated: full learning where all players learn the actual values of all model parameters before the game is played; partial learning where information is revealed after players announce whether to join the treaty, but before decisions are taken on abatement levels; and no learning where both stages of the game are played under uncertainty.

In our numerical model, we derive much more positive conclusions about the role of learning. Though uncertainty leads to an overshooting of abatement efforts and hence ignorance can pay in ecological terms, in welfare terms, this is reversed. The same conclusion remains valid once stability is explicitly accounted for. This is done by evaluating the average success over all Pareto-undominated stable coalitions under all three models of learning. Even in ecological terms learning turns out to have a positive impact in our model once we consider transfers. These transfers are designed such that they avoid a too asymmetric distribution of the gains from cooperation and they explicitly take into account the different incentives of the various world regions to leave or join a climate agreement. Under all three models of learning these transfers improve upon the success of climate agreements: larger coalitions can be stabilized and membership can be bought of regions with low abatement cost options, despite their little incentive to participate because of low benefits. The importance of transfer increases with the degree of learning. In our model this is because on average the gains from cooperation are more symmetrically distributed ex ante than ex post. Hence, without transfers, learning would have a negative impact on some regions' willingness to sign a climate treaty. The importance of transfers also increases with the degree of asymmetry between regions. Without transfers, asymmetry is an obstacle for forming large and effective agreements. With transfers, asymmetry becomes an asset. Members of the agreement benefit from exploiting the comparative advantage of cooperation. This constitutes a significant counterpoint to the omnipresent free-rider incentive caused by the public good nature of climate change mitigation.

The last point suggests one avenue of future research. Under the Kyoto Protocol and probably also in future climate treaties transfers are not paid in a lump sum fashion as we assumed. However, transfers are implicitly part of the emission permit trading system under the Kyoto Protocol, the European Trading System (EU-TS) and most likely a future US-Trading system. Hence, it will be important to work out how the structure of the transfer scheme which we considered in our analysis can be replicated through the allocation of permits if they are given out for free or how the auction mechanism has to be designed if emitters are expected to bid for emission rights

Another point we deem important in future research concerns the role of learning. First, learning could be modeled as a dynamic process in which agents update beliefs in a Bayesian sense. Second, the possibility that agents can invest in learning and the effect on endogenous technological change could be integrated in the analysis. Both points would also suggest to depart from the assumption of fixed membership and to allow for the revision of membership in a climate agreement over time as considered for instance in Ulph (2004) and Rubio and Ulph (2007). No doubt this will require major conceptual and computational advances in the theory of dynamic coalition formation with heterogeneous players.

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Appendix: Parameters of the Applied Model

Payoffs are the net present value of the stream of abatement as specified in equation (6) in the text. Benefits from abatement equal the net present value (in period *t*) of future avoided damages:

$$B_{it}(q_t;Z_{iB}) = \sum_{s=t}^{\infty}\left\{D_{is}\left(0;Z_{iB}\right) - D_{is}\left(q_t;Z_{iB}\right)\right\} \ .$$

Damages are a linearized link between abatement and climate impacts: $D_{is}(q_t;Z_{iB}) = \gamma_i + s_i \cdot \omega_{s-t} \cdot q_t \cdot \gamma_D \cdot Y_s$ where γ_i is a scaling parameter that has no effect on benefits as it cancels out, s_i are regional damage shares, $\omega_{s\text{-}t}$ reflects the fraction of emissions in period *t* still in the atmosphere in period *s*, calculated as $\omega_{s\text{-}t} = 0.64 \cdot \left(1-0.00866\right)^{s-t}$ (cf. Nordhaus 1994). Furthermore, Y_t is global GDP (projections taken from the MIT-EPPA model; Paltsev et al. 2005) and γ_D is the stochastic scale parameter of global damages as given below.

Concentration of CO_2 starts at an exogenous level of 390 ppm in 2010; the final period concentration level is then calculated by adding global emissions (E) minus abatement (q) between 2011 and 2110, taking into account their decay: $M_{2110} = M_{2010} + \sum_{s=2011}^{2110}\left\{\omega_{2110-s} \cdot \left(E_s - q_s\right)\right\}$.

Abatement costs are formulated following Ellerman and Decaux (1998), adjusted for an exogenous technological progress parameter (ς =0.005) to reflect the dynamic nature of our model:

$$C_{it}(q_{it};Z_{iC}) = \tfrac{1}{3} \cdot \alpha_i \cdot (1\text{-}\varsigma)^t \cdot q_{it}^3 + \tfrac{1}{2} \cdot \beta_i \cdot (1-\varsigma)^t \cdot q_{it}^2$$

The distribution functions of the stochastic parameters are described in detail in Dellink et al. (2008) and are reproduced here.

Table A1: Characteristics of the 2-sided Exponential Distribution Function of the Global Benefit Parameter γ_D.

	Value
5% density	-9 \$/tC
Mode	5 \$/tC
density at mode	13%
95% density	245 \$/tC
Mean	77 \$/tC

Table A2: Characteristics of the Gamma Distribution Function of Regional Benefit Shares s_i

Region	Lower bound	Mean Calibration I (Scenarios 1 to 4)	Standard deviation	Mean Calibration II (Scenario 5)
USA	0	0.2263	0.1414	0.124
JPN	0	0.1725	0.1078	0.114
EEC	0	0.2360	0.1475	0.064
OOE	0	0.0345	0.0216	0.017
EET	0	0.0130	0.0130	0.013
FSU	0	0.0675	0.0675	0.035
EEX	0	0.0300	0.0300	0.030
CHN	0	0.0620	0.0620	0.062
IND	0	0.0500	0.1000	0.171
DAE	0	0.0249	0.0498	0.085
BRA	0	0.0153	0.0306	0.052
ROW	0	0.0680	0.1360	0.233

Table A3: Characteristics of the Normal Distribution of the Abatement Cost Parameters α_i and β_i.

	α_i		β_i	
Region	Mean	Standard deviation	Mean	Standard deviation
USA	0.00050	0.00006	0.00398	0.00050
JPN	0.01550	0.00194	0.18160	0.02270
EEC	0.00240	0.00030	0.01503	0.00188
OOE	0.00830	0.00104	0.00000	0.00000
EET	0.00790	0.00198	0.00486	0.00122
FSU	0.00230	0.00058	0.00042	0.00011
EEX	0.00320	0.00080	0.03029	0.00757
CHN	0.00007	0.00002	0.00239	0.00060
IND	0.00150	0.00038	0.00787	0.00197
DAE	0.00470	0.00118	0.03774	0.00944
BRA	0.56120	0.14030	0.84974	0.21244
ROW	0.00210	0.00053	0.00805	0.00201

Table 1: Outcome of Coalition Formation and Learning: Base Scenario*

Coalition	*Global Welfare (bln US$)*	*Concentration (giga tons carbon)*
	No Learning	
Nash Equilibrium	10,427.9	1,432.2
Social Optimum	29,490.6	1,248.4
	No Transfers	
BPSC (JPN, EEC) [1]	10,910.9	1,428.5
Global Performance	10,910.9	1,428.5
	Transfers	
BPSC (USA, EET, CHN IND, DAE) [105]	18,940	1,374.8
Global Performance	15,385.8	1,398.4
	Partial Learning	
Nash Equilibrium	14,702.7	1,445.4
Social Optimum	43,348.3	1,287.6
	No Transfers	
BPSC (JPN, EEC) [1]	15,475.3	1,442.1
Global Performance	15,475.3	1,442.1
	Transfers	
BPSC (USA, EET, CHN, IND, ROW) [41]	29,374.8	1,387.8
Global Performance	24,342.6	1,407.7
	Full Learning	
Nash Equilibrium	14,702.7	1,445.4
Social Optimum	43,348.3	1,287.6
	No Transfers	
HSLC (JPN, EEC) [0.237]	15,475.3	1,442.1
Global Performance	15,142.7	1,443.1
	Transfers	
HSLC (EEC, OOE, EET, EEX, CHN, IND, DAE, BRA, ROW) [0.159]	34,788.1	1,362.7
Global Performance	30,795.9	1,381.6

* Calibration of Base Scenario see section 3. This implies in particular a discount rate of $r = 0.02$, benefit shares with mean values under Calibration I and standard deviations as listed in Table A2. Global Welfare: sum of discounted expected payoffs over all regions in bln US$ in 2010; Concentration: expected concentration in giga tons carbon in 2110; Nash Equilibrium corresponds to singleton coalition structure; Social Optimum corresponds to all regions forming the grand coalition; BPSC=best performing stable coalition in terms of expected global welfare under no and partial learning with [..] the total number of stable non-trivial coalitions; HSLC=coalition with the highest stability likelihood under full learning among all possible coalitions with [..] the stability likelihood of this coalition; Global Performance: expected global welfare and expected concentration over all Pareto-undominated stable coalitions as explained in section 2; all numbers are rounded to the first digit.

Table 2: Outcome of Coalition Formation and Learning: Lower Discount Rate Scenario*

Coalition	*Global Welfare (bln US$)*	*Concentration (giga tons carbon)*
	No Learning	
Nash Equilibrium	36,989.3	1412.3
Social Optimum	100,758.3	1178.9
	No Transfers	
BPSC (JPN, EEC) [1]	38,674.7	1,407.3
Global Performance	38,674.7	1,407.3
	Transfers	
BPSC (USA, EET, CHN, IND, DAE) [105]	65,796.3	1,337.9
Global Performance	53,765.8	1,368.3
	Partial Learning	
Nash Equilibrium	50,903.8	1,430.3
Social Optimum	142,106.9	1,236.5
	No Transfers	
BPSC (JPN, EEC) [1]	53,571.8	1,425.9
Global Performance	53,571.8	1,425.9
	Transfers	
BPSC (USA, EET, EEX, CHN, IND) [54]	93,209	1,364.3
Global Performance	75,858.5	1,391.2
	Full Learning	
Nash Equilibrium	50,903.8	1,430.3
Social Optimum	142,106.9	1,236.5
	No Transfers	
HSLC (JPN, EEC) [0.246]	53,571.8	1,425.9
Global Performance	52,211.2	1,426.7
	Transfers	
HSLC (USA, OOE, EET, EEX, CHN, IND, DAE, BRA, ROW) [0.162]	116,736.6	1,321.8
Global Performance	101,431.7	1,349.9

* Calibration of "Lower Discount Rate Scenario" see section 3. This implies a discount rate of $r = 0.01$ instead of $r = 0.02$ as assumed in the Base Scenario; all other assumptions are the same. Notation: see Table 1.

Table 3: Outcome of Coalition Formation and Learning: Higher Discount Rate Scenario*

Coalition	*Global Welfare (bln US$)*	*Concentration (giga tons carbon)*
	No Learning	
Nash Equilibrium	4,093.4	1,442.9
Social Optimum	11,924.6	1,287
	No Transfers	
BPSC (JPN, EEC) [1]	4,288.1	1,439.8
Global Performance	4,288.1	1,439.8
	Transfers	
BPSC (USA, EET, CHN, IND, DAE) [109]	7,608	1,394.2
Global Performance	6,137.4	1,414.2
	Partial Learning	
Nash Equilibrium	5,826.3	1,453.7
Social Optimum	17,925.1	1,317.8
	No Transfers	
BPSC (JPN, EEC) [1]	6,140,9	1,450.9
Global Performance	6,140.9	1,450.9
	Transfers	
BPSC (USA, EET, CHN, IND, ROW)) [35]	12,013.7	1,404.8
Global Performance	10,085.7	1,420.2
	Full Learning	
Nash Equilibrium	5,826.3	1,453.7
Social Optimum	17,925.1	1,317.8
	No Transfers	
HSLC (JPN, EEC) [0.247]	6,140.9	1,450.9
Global Performance	6,005.9	1,451.8
	Transfers	
HSLC (USA, OOE, EET, EEX, CHN, IND, DAE, BRA, ROW) [0.16]	14,605.1	1,380.4
Global Performance	12,578	1,399.3

* Calibration of "Higher Discount Rate Scenario" see section 3. This implies a discount rate of $r = 0.03$ instead of $r = 0.02$ as assumed in the Base Scenario; all other assumptions are the same. Notation: see Table 1.

Table 4: Outcome of Coalition Formation and Learning: Higher Variance of Regional Benefit Shares Scenario*

Coalition	*Global Welfare (bln US$)*	*Concentration (giga tons carbon)*
	No Learning	
Nash Equilibrium	10,427.9	1,432.2
Social Optimum	29,490.6	1,248.4
	No Transfers	
BPSC (JPN, EEC) [1]	10,910.9	1,428.5
Global Performance	10,910.9	1,428.5
	Transfers	
BPSC (USA, EET, CHN, IND, DAE) [105]	18,940	1,374.8
Global Performance	15,385.8	1,398.4
	Partial Learning	
Nash Equilibrium	12,899.7	1,454.4
Social Optimum	47,127	1,295.9
	No Transfers	
BPSC (JPN, EEC) [1]	13,815.6	1,451
Global Performance	13,815.6	1,451
	Transfers	
BPSC (USA, EEC, EET, EEX, CHN, IND, ROW) [9]	35,757	1,359.2
Global Performance	30,168.4	1,382.4
	Full Learning	
Nash Equilibrium	12,899.7	1,454.4
Social Optimum	47,127	1,295.9
	No Transfers	
HSLC (JPN, EEC) [0.143]	13,815.6	1,451.0
Global Performance	13,210.4	1,452.6
	Transfers	
HSLC (grand coalition) [0.217]	47,127	1,295.9
Global Performance	38,156.1	1,352.5

* Calibration of case “Higher Variance of Regional Benefits” see section 3. This implies a higher variance of regional benefits than assumed in the Base Case (standard deviation doubled as listed in Table A2); all other assumptions are the same. Notation: see Table 1.

Table 5: Outcome of Coalition Formation and Learning: Different Regional Benefit Shares Scenario*

Coalition	*Global Welfare (bln US$)*	*Concentration (giga tons carbon)*
	No Learning	
Nash Equilibrium	10,224.5	1,433.5
Social Optimum	29,490.6	1,248.4
	No Transfers	
BPSC (JPN, BRA, ROW) [1]	10,829.9	1,429
Global Performance	10,829.9	1,429
	Transfers	
BPSC (USA, EET, CHN, ROW) [53]	18,850.1	1,374.2
Global Performance	15,456.6	1,399.3
	Partial Learning	
Nash Equilibrium	14,360.3	1,448.7
Social Optimum	43,348.3	1,287.6
	No Transfers	
BPSC (IND, BRA, ROW) [1]	16,958.3	1,439.8
Global Performance	16,958.3	1,439.8
	Transfers	
BPSC (EEC, OOE, EET, FSU, CHN, IND, ROW) [19]	33,796.5	1,374.1
Global Performance	27,988.3	1,396.7
	Full Learning	
Nash Equilibrium	14,360.3	1,448.7
Social Optimum	43,348.3	1,287.6
	No Transfers	
HSLC (JPN, BRA) [0.128]	14,484	1,448.3
Global Performance	14,552.4	1,447.6
	Transfers	
HSLC(grand coalition) [0.15]	43,348.3	1,287.6
Global Performance	36,221.4	1,371.8

* Calibration of "Different Regional Benefit Shares Scenario" see section 3. This implies regional benefit shares according to Calibration II, Table A2, which differ from Calibration I in the Base Scenario; all other assumptions are the same. Notation: see Table 1.