UNIVERSITY OF STIRLING

DIVISION OF ECONOMICS
STIRLING MANAGEMENT SCHOOL

The Role of Uncertainty and Learning for the Success of International Climate Agreements

Michael Finus

Pedro Pintassilgo

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Michael Finus*

and

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Abstract

Technological developments intensify linkages between nations, making unilateral policies less effective. Though transnational externalities (e.g. trade, contagious diseases and terrorism) warrants coordination and cooperation between governments, this proves some times difficult. This is particularly true for international environmental agreements. One reason for meager success is the public good character of environmental protection encouraging free-riding. Another reason one might suspect are the large uncertainties surrounding most environmental problems, and in particular climate change, providing sufficient excuse to remain inactive. Paradoxically, some recent papers have concluded just the opposite: the veil of uncertainty can be conducive to the success of international environmental cooperation. This sheds serious doubts on the benefits from research on better understanding environmental impacts. In this paper, we explain why and under which conditions such a pessimistic conclusion can be true. However, taking a broader view, we argue that these unfavorable conditions are rather an exception than the rule. Most important, we suggest a mechanism that mitigates the negative effect of learning and which may even turn it into a positive effect. Our results apply beyond the specifics of climate change to similar problems of cooperation in the presence of externalities.

Keywords: cooperation, climate change, self-enforcing agreements, uncertainty, learning

JEL-Classification: C72, D62, D81, H41, Q20.

* Department of Economics, University of Stirling, Scotland, UK; **michael.finus@stir.ac.uk**.

** Faculty of Economics, University of Algarve, Faro, Portugal; ppintas@ualg.pt. The research has been conducted while Pedro Pintassilgo was a visiting scholar at the Department of Economics, University of Stirling. He would like to acknowledge the hospitality of the department as well as financial support by the Portuguese Foundation for Science and Technology (FCT), grant no. BSAB/735/ 2007.

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1. Introduction

Technological developments intensify linkages between nations, making unilateral policies less effective. Though transnational externalities (e.g. trade, contagious diseases and terrorism; see e.g. Sandler 2004 and Yi 1996) warrants coordination and cooperation between governments, this proves some times difficult. One of the greatest challenges to international co-operation the world is currently facing is climate change, as emphasized by the two prominent studies, the Stern and the IPCC Reports (Stern 2006 and IPCC 2007). International response to this challenge can be traced back to 1988 when the IPCC was founded – an international body that gathers and synthesizes current world-wide scientific evidence on climate change. However, it was not until 1997 that 38 countries agreed to specific emission ceilings under the Kyoto Protocol, which was not ratified before 2002, after several concessions had been granted to various participants and after the US had declared that it would withdraw from the treaty altogether. Currently, a "Post-Kyoto" agreement for the period after 2012 is being negotiated, with the aim to tighten emission limits, encourage the participation of the US and the "new" emerging polluters China and India.

One important problem for effective cooperation is free-riding. For a common property resource this well-known since Hardin (1968) and has been reiterated in the specific context of self-enforcing international environmental agreements (SEIEAs) by Barrett (1994), Carraro and Siniscalco (1993) and Hoel (1992). Later papers, using richer models, either with an empirical (e.g. Bosello et al. 2003, Finus and Tjøtta 2003 and Weikard et al. 2006) or theoretical (e.g. Asheim et al. 2006, Barrett 2001, 2006, and Rubio and Ulph 2007) focus, have suggested some possibilities to make SEIEAs more effective, but have confirmed the general negative conclusion more or less.[1]

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1 Surveys are provided in Barrett (2003) and Finus (2003).

Another important problem is the large uncertainty surrounding the impact of greenhouse gases on the climate and caused environmental damages. Predictions about abatement costs are also difficult (IPCC 2007 and Stern 2006). For instance, the former US President George Bush used uncertainty as one argument for his decision to withdraw from the Kyoto Protocol. In a letter to Senators, dated March 13, 2001, as quoted by Kolstad (2007), he wrote: "I oppose the Kyoto Protocol … we must be very careful not to take actions that could harm consumers. This is especially true given the incomplete state of scientific knowledge".

Recently, a literature has emerged, which combines free-riding with uncertainty and learning, using simple SEIEA-models with a static payoff function[2] (Kolstad 2007, Kolstad and Ulph 2008, 2009 and Na and Shin 1998). Their main conclusion is that in the strategic context of the formation of climate agreements, learning leads to worse outcomes than no learning. This "negative" result, though interesting, is intriguing as it runs counter to increased research efforts on climate change world wide. This motivates the three research questions posed in this paper. What are the driving forces to generate this result? How general is this conclusion? Is there a way to fix this problem? Short answers to these questions emerging from our results are: in the context of uncertainty and coalition formation there is an information, a strategic and a distribution effect from learning; there can be instances where learning is bad if the last two effects are negative and dominate the first positive effect; these instances are rather exceptions than the rule, and if they occur, then they can be fixed through appropriate hedging strategies. For more detailed answers, it is informative to take first a wider view at some of the economic literature on uncertainty and learning.

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2 That is, it captures the public bad nature of greenhouse gases but not their dynamics as stock pollutants.

2. Literature Review and Driving Forces

In the context of incomplete information, the cases of symmetric (analytical) and asymmetric (strategic) uncertainty can be distinguished. A classical contribution showing that asymmetric uncertainty can be conducive to cooperation is Kreps et al. (1982) and the later generalization by Fudenberg and Maskin (1986). In a finitely repeated prisoners' dilemma (some small amount of) uncertainty about other players' strategies is sufficient for establishing cooperation for some time.[3]

For symmetric uncertainty, which is the framework we are considering, Iida (1993) comes mainly to a negative conclusion about the prospects of international policy coordination under uncertainty. In his informal discussion, citing many interesting examples of real world politics, he basically identifies two driving forces. First, there is a tendency to underestimate the benefits from coordination under uncertainty compared to the non-cooperative status quo.[4] Second, governments find it difficult to agree on the "correct" model. For instance, in terms of monetary policy, one government may believe in the Keynesian model, the other in the monetary model. Frankel and Rockett (1988) even argue that macroeconomic policy coordination leads to worse outcomes than if countries pursue non-cooperative policies. As Gosh and Masson (1991) point out this conclusion may be overly pessimistic if a policy choice under uncertainty is compared with the correct ex-post model. Nevertheless, even if evaluated ex-ante, if governments negotiate policy coordination based on different macroeconomic models which suggest different (and sometimes contradictory)

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3 Probably the most convincing motivation for this result is to assume uncertainty about other players' payoffs such that a conditional cooperative strategy of other players could be a rational choice. Then, at least for some time, players have an incentive pretending to follow a cooperative strategy.

4 This argument is formalized, for instance, in Fernandez and Rodrik (1991). See the discussion below.

policy conclusions, the bargaining outcome under uncertainty may be worse than no coordination.[5]

As Frankel and Rockett (1988) stress for macroeconomic policy, also in climate change the number of models, assumptions, and hence different policy conclusions, are abundant (see e.g. IPCC 2007). However, this is not the underlying problem in our model. We abstract from such controversy about optimal policy levels. This is because we assume that players have symmetric expectations about the parameters of the payoff function and policy co-ordination always pays in our public good game. However, uncertainty affects optimal policy levels, which works through the information and the strategic effect from learning, as we call it, and the distribution of the gains from cooperation, which we call the distributional effect from learning.

We consider a two-stage coalition formation game where countries choose their membership in the first stage, and their policy levels in the second stage. The game is solved backward assuming that players play a Nash equilibrium in each stage. In our model, the social optimum is reproduced if all players join the agreement (grand coalition), and the non-cooperative equilibrium if all players remain singletons (singleton coalition structure). But there are also intermediate cases of cooperation, with some though not all players joining the agreement. It is then tested in the first stage which of these coalitions are stable. Following Kolstad (2007) and Kolstad and Ulph (2008), in this setting we can not only distinguish between a no learning scenario (information is neither available in stage 1 nor 2) and a full learning scenario (all information is available before stage 1), but also a partial learning scenario (information is available before stage 2, but not before stage 1).

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5 There is also a literature that analyzes the value of information in the context of public goods (e.g. Arce and Sandler 2001 and Sandler et al. 1987) or oligopolies (e.g. Einy et al. 2003 and Vives 1984), though this is restricted to a non-cooperative setting (Bayesian Nash equilibria).

The choice of optimal policy levels of coalition members and non-members in the second stage benefits from information (information effect) but they interact strategically as long as not all players are in the agreement (strategic effect). Suppose for the sake of the argument that the grand coalition would form which chooses the policy level of the social planner. Then, the value of information through learning cannot be negative. This is in accordance with the general wisdom that "learning is good" – only the information effect is present.[6] Now suppose the singleton coalition structure would form. In this non-cooperative setting, players interact strategically and the value of information can become negative as shown in Gollier and Treich (2003) for three economic examples.

For illustrative purposes, suppose as in Ulph (1998) that all players have ex-ante symmetric expectations but turn out to be asymmetric ex-post. Assume that asymmetry means only different marginal benefit functions from global abatement, though no differences in marginal abatement cost functions from individual abatement. Then, no learning leads to a symmetric whereas learning to an asymmetric equilibrium. Both equilibria are inefficient (each country sets marginal abatement cost only equal to own but not the sum of marginal benefits) but the equilibrium under no learning is at least cost-effective (i.e. marginal abatement costs equalize). Thus the strategic effect from learning can be negative. Taken together, in our coalition model which captures not only full or no cooperation but also intermediate cases of partial learning, information and strategic effect are at work in the second stage.

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6 This would obviously also be true in a model with a dynamic payoff structure (see footnote 2) where uncertainty calls on the one hand for early action due to the irreversibility of accumulated emissions in the atmosphere, following the precautionary principle, and, on the other hand, for delayed action, anticipating cheaper abatement options in the future and to avoid log-in-effects from non-retrievable investment in abatement technology. See Kolstad (1996a, b), Gollier and Treich (2003), Ulph and Maddison (1997), and Ulph and Ulph (1997).

Finally, there is the distributional effect from learning. Generally speaking, there are two contradictory conclusions regarding this effect in the literature. Fernandez and Rodrik (1991) consider pure uncertainty about the distribution of the gains and losses from a trade policy reform which is beneficial at the aggregate. They conclude that there is a bias towards the status quo whenever gainers and losers cannot be identified beforehand, despite agents being risk neutral.

In our model, also assuming risk neutrality, when exclusively considering the case of distributional uncertainty, we find just the opposite. The intuition is along the lines of Young (1994), borrowing the concept of the veil of uncertainty from Brennan and Buchanan (1985), who argues that agreements are easier if potential participants do not know the distributional consequences. This has been illustrated in a simple two-player model in Helm (1998) and in Kolstad (2005). In our model with N players, distributional uncertainty affects the participation decision in the first stage of coalition formation. For instance, under full learning, only small coalitions are stable which renders this scenario less effective than no learning. However, we show that this problem can be mitigated, and, in fact, may even be transformed into an advantage if hedged against with an appropriate transfer scheme. Then, heterogeneity is an asset, leading to larger and more effective agreements.

Taken together, our contribution is threefold. First, we qualify the negative results of previous papers by using more general assumptions (which we make explicit in the course of the analysis). Second, we work out the driving forces (information, strategic and distributional effect) and relate them to the three learning scenarios (no, partial and full learning) and the kind of uncertainty (level, distribution or both) about the benefits from cooperation. This will stress that our results apply to many other policy problems beyond the specifics of climate change. Third, we show that if there is a negative distributional effect from learning, transfers can mitigate this effect and even transform it into a positive effect. Then diversity can be an asset.

In the following, we outline our coalition model and describe the three "learning scenarios" and three "uncertainty cases" in section 3. Section 4 derives the model solutions for stages 1 and 2 and gives already a hint regarding the driving forces that affect the overall results presented in section 5. Section 6 summarizes the main conclusions and proposes some issues for future research.

3. Model Outline

3.1 Coalition Formation Game

International environmental agreements are typical single agreements with voluntary participation and open membership, i.e. a country can neither be forced into nor excluded from participation. Therefore, we model coalition formation game as a two-stage open membership single coalition game. In the first stage, players (i.e. countries in our context) decide whether to join an agreement (i.e. a climate treaty in our context) or remain an outsider as a singleton. In the second stage players choose their policy levels (i.e. abatement in our context). The game is solved backward assuming that strategies in each stage must form a Nash equilibrium.

This game has also been called cartel formation game with non-members called fringe players. It originates from the literature in industrial organization (d' Aspremont et al. 1983) and has been applied widely in this literature (e.g. Deneckere and Davidson 1985, Donsimoni et al. 1986 and Poyago-Theotokay 1995; see Bloch 2003 and Yi 1997 for surveys) but also in the literature on self-enforcing international environmental agreements (e.g. Barrett 1994, Carraro and Siniscalco 1993 and Rubio and Ulph 2007; see Barrett 2003 and Finus 2003 for surveys).

In the first stage, players' membership decisions lead to a coalition structure, $K=\{S,\ 1_{n-m}\}$, which is a partition of players, with n being the total number of players, m the size of coalition S, $m \le n$, and N the set of players, $S \subseteq N$. Due to the simple structure of this coalition formation game, i.e. there can be at most one non-trivial coalition, coalition structure K is entirely determined by coalition S. Typically, we will denote a member of S by i and call it a signatory and a non-member of S by j and call it a non-signatory.

In the second stage, given that some coalition S has formed, players choose their abatement levels q_i in our setting.[7] The decision is based on the following payoff function:

$$\text{(1)} \qquad \Pi_i = B_i\left(\sum_{k=1}^{n} q_k\right) - C_i\left(q_i\right),\ i \in N$$

where $B_i\left(\bullet\right)$ is country i's concave benefit function from global abatement (in the form of reduced damages, e.g. measured against some business-as-usual-scenario) and $C_i\left(\bullet\right)$ its convex abatement cost function from individual abatement. The global public good nature of abatement is captured by the benefit function which depends on the sum of all abatement contributions. For a start, we assume that all functions and their parameters are common knowledge and introduce uncertainty in the next section.

Working backward, we assume that the coalition derives its optimal economic strategies in the second stage as a (coalitional) Nash equilibrium between coalition S with its m members and the $n-m$ singletons. Thereby, the coalition acts de facto as a single or meta

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7 An alternative specification of payoff functions, comprising damage cost functions from global emissions and benefit functions from individual emissions, produces equivalent results. This equivalence holds as long as non-negativity constraints are observed, as discussed for instance in Diamantoudi and Sartzetakis (2006) and Rubio and Ulph (2006).

player (Haeringer 2004). The equilibrium is derived by assuming that coalition members maximize the aggregate payoff of their coalition

$$(2) \qquad \underset{q^S}{max}.\sum_{i\in S}\Pi_i\left(S\right)\Rightarrow\sum_{i\in S}B_i^{'}\left(\sum_{k=1}^{n}q_k\right)=C_i^{'}\left(q_i\right)\;\;\forall\, i\in S$$

whereas as all singletons maximize their own payoff

$$(3) \qquad \underset{q_j}{max}.\,\Pi_j\left(S\right)\Rightarrow B_j^{'}\left(\sum_{k=1}^{n}q_k\right)=C_j^{'}\left(q_j\right)\;\;\forall\, j\notin S$$

where q^S is the vector of abatement levels of those players that belong to coalition S, $B_k^{'}$ and $C_k^{'}$ are the derivatives of B_k and C_k with respect to q_k, respectively. The simultaneous solution of first order conditions (F.O.C.s) in (2) and (3) delivers equilibrium abatement levels $q_i^*(S)$ of signatories and $q_j^*(S)$ of non-signatories. The F.O.C.s in (2) are the Samuelsson conditions for the optimal provision of a public good, though they hold only for coalition members; the F.O.C.s in (3) are those in a non-cooperative equilibrium.[8] Substituting the equilibrium abatement levels for a given coalition S into the payoff functions delivers the payoffs of signatories, $\Pi_{i\in S}^*(S)$, and non-signatories, $\Pi_{j\notin S}^*(S)$, in the second stage of the coalition formation game. This assumes no transfers. However, given the assumption of joint welfare maximization of coalition members and the fact that we allow for asymmetric payoff functions, it is perceivable that coalition members share their total payoff $\Pi_S^* = \sum_{i\in S}\Pi_i^*(S)$ through transfers t_i such that the "corrected" payoffs are $\Pi_i^*(S)+t_i$ with $\sum_{i\in S} t_i = 0$.

8 Note that if $S = N$ (i.e. all players form the grand coalition) the equilibrium abatement vector corresponds to the social optimum and if either $S=\{i\}$ or $S=\varnothing$ (i.e. all players act as singletons) this corresponds to the Nash equilibrium.

In the first stage, stable coalitions are determined by invoking the stability concept of internal and external stability, which is de facto a Nash equilibrium in membership strategies. Consider first the version without transfers:

(4) internal stability: $\Pi_i^*(S) \geq \Pi_i^*(S \setminus \{i\}) \;\; \forall\, i \in S$

(5) external stability: $\Pi_j^*(S) > \Pi_j^*(S \cup \{j\}) \;\; \forall\, j \notin S$.

That is, no signatory should have an incentive to leave coalition S to become a non-signatory and no non-signatory should have an incentive to join coalition S. In order to avoid knife-edge cases, we assume that if players are indifferent between joining coalition S and remaining outside, they will join the agreement. Coalitions which are internally and externally stable are called stable and the set is denoted by S^*. In case there is more than one stable coalition, we apply the Pareto-dominance selection criterion. We denote the set of Pareto-undominated stable coalitions by $\Psi^* \supseteq S^*$. If non-trivial coalitions are stable, they Pareto-dominate the singleton coalition structure. Note that the coalition structure comprising only singletons is stable by definition and hence existence of an equilibrium is guaranteed.[9]

In the case of transfers, many schemes are perceivable which typically lead to different sets of stable coalitions. In order to avoid this sensitivity, we follow the concept of an almost ideal sharing scheme (AISS) proposed by Eyckmans and Finus (2009). They argue that if and only if:

(6) potential internal stability: $\sum_{i \in S} \Pi_i^*(S) \geq \sum_{i \in S} \Pi_i^*(S \setminus \{i\})$

[9] The reason is that the singleton coalition structure can be generated by $S = \emptyset$, i.e. all players announce not to join the agreement. Then if one player changes her announcement, such that $\tilde{S} = \{i\}$, the coalition structure remains the same.

holds, then there exists a transfer system which makes S internally stable. A transfer system for which every potentially internally stable coalition is internally stable belongs to the AISS, which gives each coalition member its free-rider payoff, $\Pi_i^*(S\setminus\{i\})$, plus some positive share of the surplus $\sigma(S)=\sum_{i\in S}\Pi_i^*(S)-\sum_{i\in S}\Pi_i^*(S\setminus\{i\})$. For every transfer system belonging to the AISS coalition S is externally stable if and only if all larger coalitions $S\cup\{j\}$, including a fringe player $j\notin S$, are not potentially internally stable. Consequently, for every transfer system in this class the set of internally, externally and hence stable coalitions is the same. Most important, among those coalitions that can be potentially internally stabilized (which may not be possible for large coalitions), i.e. $\sigma(S)\geq 0$, AISS stabilizes (in the sense of internal and external stability) those with the highest aggregate welfare over all players. Their conclusion hinges on only one structural property, namely the property of (weakly) positive externalities from coalition formation. It means that whenever a non-signatory j joins coalition S, such that $S\cup j$ forms, non-members are better or at least not worse off. It is straightforward to prove that this property (in its strong version) holds in our cartel formation game where players choose abatement strategies according to (2) and (3) based on payoff function (1).

3.2 Three Learning Scenarios

We now assume that some parameter values of the payoff functions are uncertain. Following Kolstad and Ulph (2008, 2009), we assume risk-neutral agents as players are governments and not individuals, and distinguish three *learning scenarios*: 1) full learning, 2) partial learning and 3) no learning. *F*ull *L*earning (abbreviated FL) can be considered as a benchmark case in which players learn about the true parameter values before taking the membership decision in the first stage. Hence, uncertainty is fully resolved at the beginning of the game. For *P*artial *L*earning (abbreviated PL) it is assumed that players decide about membership under uncertainty but know that they will learn about the true parameter values before deciding upon abatement levels in the second stage. Hence, the membership decision is based on expected payoffs, under the assumption that players will take the correct decision in the second stage. Finally, under *No Learning* (abbreviated NL) also the abatement decision has to be taken under uncertainty. That is, players derive their abatement strategies by maximizing expected payoffs. The membership decisions are also taken based on expected payoffs, though these payoffs differ from those under partial learning, given that less information is available.

It is worthwhile pointing out that our assumption implies that learning takes the form of perfect learning (Kolstad and Ulph 2008, 2009). That is, if players learn about parameter values, no uncertainty remains. Hence, partial learning is de facto delayed learning, though we stick to the terminology introduced by Kolstad and Ulph. Full learning is certainly an optimistic and no learning a pessimistic benchmark about the role of learning in the context of climate change. Partial learning approximates (because beliefs are not updated in a Bayesian sense) the fact that information becomes available over time. For instance, between the signature of the Kyoto Protocol in 1997, and its entry into force in 2002, with compliance in 2008-12, more information has emerged, as documented by various updated issues of IPCC reports.

3.3 Three Uncertainty Cases

3.3.1 Introduction

We now turn to the assumption about the uncertain parameters of the payoff functions which are summarized in three *uncertainty cases*. Due to the complexity of coalition formation and the three effects mentioned in the Introduction, the consideration of a particular payoff function, as well as the parameters that are uncertain and their distributions is required. In order to avoid the exclusive focus on the binary equilibrium choices "abate" or "not abate" in the second stage, as for instance in Kolstad (2007) and Kolstad and Ulph

(2008, 2009), and to capture the information and the strategic effect, we consider a strictly concave payoff function which is still simple enough to derive analytical results:[10]

$$(7) \qquad \Pi_i = b_i \sum_{k=1}^{n} q_k - c_i \frac{q_i^2}{2} \ , \ i \in N \, , \ b_i > 0 \, , \ c_i > 0$$

where b_i is a benefit parameter, $b_i \sum_{k=1}^{n} q_k$ is the benefit from global abatement, c_i is a cost parameter, and $c_i \frac{q_i^2}{2}$ is the abatement cost from individual abatement.

Generally, the benefit as well as the cost parameters could be uncertain. However, following Kolstad (2007), Kolstad and Ulph (2008, 2009) and Na and Shin (1998), in the climate context uncertainty about the benefits from reduced damages appears to be more important than uncertainty about abatement costs. Hence, we simplify the model, by dividing payoffs by the cost parameter c_i, define the benefit-cost ratio by $\gamma_i = b_i / c_i$, and hence payoff function (7) reads:

$$(8) \qquad \Pi_i = \gamma_i \sum_{k=1}^{n} q_k - \frac{q_i^2}{2} \ , \ i \in N \, , \ \gamma_i > 0 \ .$$

Henceforth, we call γ_i the benefit parameter. If this parameter is uncertain, then it is represented by the random variable Γ_i, with associated distribution f_{Γ_i}. The assumptions regarding our three uncertainty cases are displayed in Table 1.

10 A similar payoff function has been used for instance by Barrett (2006) and Na and Shin (1998) but also by many others.

Table 1: Three Uncertainty Cases about the Benefit Parameters

Case	Ex-ante Expectations of Parameters	Ex-post Realizations of Parameters	Interpretation of Parameters	Uncertainty about
1	symmetric	symmetric	common	level of benefits
2	symmetric	asymmetric	individual	distribution of benefits
3	symmetric	asymmetric	common and individual	level and distribution of benefits

In all three cases, uncertainty is symmetric as all players know as much or little about their own as about their fellow players' payoff functions. We first lay out the specific assumptions and then provide a wider interpretation.

3.3.2 Assumptions

Case 1: Uncertainty about the Level of Benefits

The setting of case 1 is considered in Kolstad (2007) and Kolstad and Ulph (2008, 2009), which the authors call systematic uncertainty as it relates to a *common parameter*. All players have the same expectations ex-ante, and once uncertainty is resolved, all countries have the same benefit parameter ex-post, which we call symmetric realization, i.e. $\Gamma_i = \Gamma_k$ $\forall\, i, k \in N$. Thus, uncertainty is correlated. However, we find it more illuminating to point out that in this case uncertainty is de facto about the *level of the benefits* from global abatement. For the later analysis, it is helpful to point out that this implies that the sum of marginal benefits is uncertain with a positive variance.

Compared to the studies mentioned above, our case 1 appears to be more general in two respects. First, our payoff function does not restrict abatement strategies to a binary choice and hence optimal abatement strategies are a function of the benefit parameter, a prerequisite for the information and strategic effect to work. Second, we do not assume any particular distribution for the uncertain benefit parameters.

Case 2: Uncertainty about the Distribution of Benefits

The setting of case 2 is considered in Na and Shin (1998); uncertainty relates to *individual parameters*. Though expectations about the benefit parameters are symmetric, their realizations are asymmetric among players. Like in Na and Shin (1998), we consider that the random variables Γ_i, $\forall\, i \in N$, are perfectly correlated across all players. Unlike the model of Na and Shin (1998) with three players, we consider an arbitrary number of players. Because of the larger complexity, we adopt a specific distribution for parameter Γ_i, namely a uniform distribution:

(9) $$f_{\Gamma_i}(\gamma_i) = \begin{cases} \dfrac{1}{n} & for \quad \gamma_i = k,\ k \in N \\ 0 & otherwise \end{cases}$$

which implies expected value, $E[\Gamma_i]$, and variance, $Var[\Gamma_i]$, as follows:

(10) $$E[\Gamma_i] = \frac{n+1}{2} \text{ and } Var[\Gamma_i] = \frac{n^2-1}{12}.$$

We model perfect correlation by assuming that all players have a different benefit parameter: $\Gamma_i \neq \Gamma_k$, $\forall\, i \neq k \in N$. Thus, vector $\Gamma = (\Gamma_1,...,\Gamma_n)$ is composed of all the elements of N, i.e. $\bigcup_{i=1}^{n} \Gamma_i = N$. The sum of marginal benefits is fixed and consequently its variance is zero.

Here perfect correlation implies that uncertainty is purely about the *distribution of the benefits* from global abatement as the level of global benefits is constant. That is, vector Γ can be viewed as different shares of the global benefits from abatement, as for instance modeled in Dellink et al. (2008).[11] Different from Na and Shin (1998), we also consider the case of partial learning and most important, the possibility to mitigate asymmetries through transfers, which, as we show later, plays a crucial role for the outcome under full learning.

Case 3: Uncertainty about the Level and Distribution of Benefits

Case 3 is a combination of the previous two cases and hence there is uncertainty about *common and individual parameters*. This translates in our setting into uncertainty about the *level and distribution* of the benefits from global abatement. This is captured by assuming the same uniform distribution as in case 2, except that all random variables, Γ_i, $i = 1,...,n$, are identically and independently distributed, and therefore uncorrelated. Hence, the sum of marginal benefits is uncertain with positive variance which is larger than in case 2, but smaller than in case 1. Different from Kolstad and Ulph (2009) our distribution allows for more than two values of the random variables, abatement strategies are not binary and, again, most important we study the role transfers.

3.3.3 Interpretation of the Three Uncertainty Cases

All three cases capture an important aspect of the uncertainty surrounding climate change. There is much uncertainty about the absolute level of the benefits from reduced damages but also much debate about their regional distribution: which countries will be suffering more from climate change? (Tol 2005). Hence, case 3 is the most comprehensive case, but cases 1 and 2 are useful benchmarks in order to isolate effects. As the random variable Γ_i is the benefit-cost ratio and the only variable in this simple model, it exclusively determines the gains from cooperation. Hence, we de facto model uncertainty about the level and/or

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11 Let $\gamma_i = \lambda_i \sum_{k=1}^{n} \gamma_k = \lambda_i L$ where λ_i denotes the share of global benefits of player i, with $\sum_{k=1}^{n} \lambda_k = 1$, and $L = \sum_{k=1}^{n} \gamma_k$ the level of global benefits. Then, in case 2 $L = n(n+1)/2$, and $\lambda_i = 2j/(n(n+1))$, $j \in \{1,2,...,n\}$.

distribution of the gains from cooperation – a problem which certainly applies to many economic problems with externalities.

A common feature of all three cases is that there is not only symmetric uncertainty, but all players share the same beliefs about the distribution of the uncertain parameter and consequently are ex-ante symmetric. This is a simplification and requires that some coordination has taken place ex-ante on which we comment in section 6. It avoids the problems of disagreement about optimal policy levels under uncertainty as mentioned in the Introduction. Even under learning, with possible asymmetric realizations of the random variables in cases 2 and 3, disagreement about policy levels is not an issue, as coalition members maximize their joint welfare. However, disagreement will figure in indirectly when it comes to decide on the participation in the agreement. Then, under full learning, asymmetry causes little participation if not balanced by transfers. The degree of ex-post asymmetry increases from our case 1 (no asymmetry) over case 3 (some asymmetry) to case 2 (maximum asymmetry). In contrast, under partial and no learning, participation is based on expected payoffs which are symmetric for our assumptions.

4. Model Solution

In this section, we solve the model for the three learning scenarios and the three uncertainty cases. As pointed out above, we solve the game backward, starting with the second stage.

4.1 Second Stage of Coalition Formation

In the full and partial learning scenarios, players know the realization of the random variables Γ_k, which are denoted as γ_k. Hence, given that a coalition structure $K = \left\{S, 1_{(n-m)}\right\}$ has formed in the first stage, the optimal abatement levels of the members of coalition S and the singletons $j \notin S$ follow from the maximization procedure described in (2) and (3), based on payoff function (8), which delivers:

(11) $$q_i^*(S)=\sum_{\ell\in S}\gamma_\ell \;\; \forall\, i\in S\,,\; q_j^*(S)=\gamma_j \;\; \forall\, j\notin S\,,\; Q^*(S)=m\sum_{i\in S}\gamma_i+\sum_{j\notin S}\gamma_j$$

with $Q^*(S)$ denoting total abatement. Hence, total abatement increases in the benefit parameter and in the size of the coalition.

In the no learning scenario, players do not know the realization of the random variables Γ_k. Hence, they derive their equilibrium abatement levels from taking expectations over the payoffs in (2) and (3), respectively, and maximizing these expected payoffs. As payoffs are linear in the random variables Γ_k, certainty equivalence holds. That is, maximization of expected payoffs is equivalent to the maximization of payoffs under certainty for $\gamma_k = E[\Gamma_k]$. This delivers equilibrium abatement levels:

(12) $$q_i^{**}(S)=\sum_{i\in S}E[\Gamma_i] \;\; \forall\, i\in S\;,\; q_j^{**}(S)=E[\Gamma_j] \;\; \forall\, j\notin S\,,$$
$$Q^{**}(S)=\left(m^2-m+n\right)E[\Gamma_k]$$

where we use two asterisks in order to stress the difference to full and partial learning. Note that (12) are also the expected abatement levels. Again total expected abatement increases in the coalition size and the expected benefit parameter.

Despite the fact that we have not yet determined stable coalitions in the first stage, for the three learning scenarios and the three uncertainty cases, it is already informative to conduct a comparison of the outcomes of the second stage. This allows us to isolate the information and strategic effect from the distributional effect in a first step. In a second step, our analysis of the size of stable coalitions, presented in the next subsection, will allow us to isolate the distributional effect. Both steps provide useful information for the interpretation of the overall outcome discussed in section 5.

For the first step, we take an ex-ante perspective and compute expected abatement also in the cases of full and partial learning. Ex-ante, players do not know whether they are signatories or non-signatories. For a coalition with m members, the probability of being a signatory is m/n and the probability of being a non-signatory is $(n-m)/n$ as all players are ex-ante symmetric. Consequently, expected individual abatement is computed as m/n times the expected abatement of a signatory plus $(n-m)/n$ times the expected abatement of a non-signatory, or, equivalently, $1/n$ times expected total abatement. Hence, relations between the three learning scenarios in terms of expected individual abatement follows immediately from the relation of expected total abatement. The same link holds for expected payoffs which we analyze below.

Proposition 1: Expected Abatement in the Second Stage

Let $K=\{S,1_{n-m}\}$ *be some coalition structure with coalition* S *of size* m. *Under all three learning scenarios, and all three uncertainty cases, the following relation holds for expected total abatement and expected individual abatement levels:*

$$FL = PL = NL\,.$$

Proof: Follows immediately from (11) and (12). **(Q.E.D.)**

From Proposition 1 it is evident that in our model differences (similarities) between the three learning scenarios in terms of the overall outcome of coalition formation with respect to abatement – analyzed in section 5 – must exclusively stem from different (the same) stable coalition(s). This is obvious for full and partial learning as they are anyway identical in the second stage. As suggested by Proposition 1, this also holds for no learning in our model.

By inserting equilibrium abatement levels (11) into payoff functions in the case of full and partial learning, and taking expectations over the random variable Γ_i, we can compute expected payoffs. A similar procedure applies to no learning by using (12).

Proposition 2: Expected Payoffs in the Second Stage

Let $K = \{S, 1_{n-m}\}$ *be some coalition structure with coalition* S *of size* m. *Then for the three learning scenarios the following relations hold for expected total payoffs and expected individual payoffs:*

Case 1: $FL = PL > NL$

Case 2: $FL = PL \leq NL$ *with strict inequality if* $S \neq N$

Case 3: $FL = PL > NL$.

Proof: See Appendix 1. **(Q.E.D.)**

The intuition behind Proposition 2 is quite informative for the understanding of the driving forces of our model. First, as mentioned above, full and partial learning are identical as there is no difference in the second stage. On the one hand, this suggests that differences or similarities between this two learning scenarios in terms of overall success can exclusively be attributed to stability in the first stage and must stem from the distributional effect. On the other hand, full and partial learning can be summarized under the heading of learning for the subsequent comparison with no learning.

Second, consider the grand coalition, $S = N$. Then the strategic effect is zero by definition. The first order conditions require setting the sum of marginal benefits over all players equal to individual marginal abatement costs. Under no learning, the sum of marginal benefits is unknown in uncertainty cases 1 and 3 as there is uncertainty about the level of benefits. However, in case 2 this information is available as there is only uncertainty about the distribution of benefits. Therefore, the information effect from learning is positive in case 1 and 3, but is zero in case 2.

Third, consider any coalition different from the grand coalition, $S \neq N$. Hence, the strategic effect is not necessarily zero anymore. Moreover, also in case 2, under no learning, neither do non-signatories know their individual marginal benefits nor do signatories know the sum of marginal benefits of their coalition. Hence, also in case 2, the information effect from learning is positive.

Now consider case 1. Under no learning, equilibrium expected abatement either implies a systematic overshooting or undershooting of abatement levels compared to learning. Systematic means that signatories and non-signatories abatement levels are simultaneously either too high or too low. This relates to the systematic uncertainty about a common parameter, which is about the level of benefits. Though overshooting implies higher benefits, this is costly due to convex abatement costs. Overall, the net gain from overshooting is smaller than the net loss of undershooting and hence learning leads to higher expected total and individual payoffs than no learning. Hence, together the information and strategic effect from learning are positive.

Now consider case 2. Lack of information still leads to over- and undershooting, but this is not systematic anymore as there is only uncertainty about the distribution but not the level of benefits. Overshooting of signatories is accompanied by undershooting of non-signatories and vice versa under no learning. This translates into a smaller variation of signatories' and non-signatories' abatement levels compared to learning. Because all players have the same abatement cost function, this translates into lower expected costs under no learning than under learning (though expected benefits are the same). Hence, the strategic effect is related to cost-effectiveness in our model; it is stronger and works in the opposite direction of the information effect from learning.

Since case 3 combines features of case 1 and 2, it also combines the driving forces of both cases. For our model assumptions, it turns out that the features of case 1 dominate and hence we have the same ranking as in case 1.

3.2 First Stage of Coalition Formation

In this section, we determine stable coalitions based on the equilibrium abatement strategies derived for the second stage. Now we have to distinguish also between full and partial learning because under partial learning the realizations of the random variables are not known in the first stage. Nevertheless, the expected payoffs under partial learning are different from those under no learning as players have more information. Subsequently, we skip all technical details which we provide in Appendix 2. Moreover, since the interplay between signatories and non-signatories requires at least three players, we henceforth assume $n \geq 3$.

We start with the cases of partial and no learning as they do not require distinguishing between no transfers and transfers. This is because for each of these scenarios expected individual payoffs within the group of signatories and within the group of non-signatories are the same. Hence, transfers cannot improve upon stable coalitions.

Proposition 3: Equilibrium Coalitions under Partial and No Learning

Under the partial and the no learning scenario, in uncertainty cases 1, 2 and 3, the expected equilibrium coalition size $E[m^*]$ *without and with transfers is given by:* $E\left[m^{*PL}\right] = E\left[m^{*NL}\right] = 3$.

For no learning the intuition is straightforward. As pointed out above, due to certainty equivalence, equilibrium abatement levels under no learning correspond to those under certainty if the parameters γ_k are equal to the expected value of Γ_k. Due to ex-ante symmetric expectation in all three uncertainty cases, the expected value is the same for all players. Thus, the outcome is the same as that of a game with certainty and symmetric payoff functions. For payoff function (8) and symmetric players it is well-known from the literature (see e.g. Finus 2003) that the stable coalition comprises three signatories if

$n \geq 3$.[12] Also under partial learning the ex-ante symmetry leads to the same stable coalitions, though certainty equivalence does not hold. In other words, in our model, the information and strategic effect work only through the second stage but do no affect the stability in the first stage. Hence, only differences in the second stage can explain differences in the final outcome between partial and no learning.

In the full learning scenario, ex-post realizations are symmetric in uncertainty case 1. Hence, we also do not require considering transfers and get the same size of stable coalitions as in the no and partial learning scenario. This is different in uncertainty cases 2 and 3. Therefore, without transfers, stable coalitions are smaller, but with transfers this can be quite different.

Proposition 4: Equilibrium Coalitions under Full Learning

Under the full learning scenario, the expected equilibrium coalition size $E[m^{*FL}]$ *is given by:*

<u>*Uncertainty Case 1: No Transfers and Transfers*</u>

$E\left[m^{*FL}\right]=3$ *where all possible 3-player coalitions are stable.*

<u>*Uncertainty Case 2: No Transfers*</u>

$$E\left[m^{*FL}\right]=\begin{cases}1 & if \quad n=3\\ 2 & if \quad n\geq 4\end{cases}$$

<u>*Uncertainty Case 2: Transfers*</u>

$$E\left[m^{*FL}\right]=\begin{cases}3 & if \quad n\leq 8\\ f(n)>3 & if \quad n\geq 9\end{cases}$$

where in the case of no transfers, for $n \geq 4$*, the only stable coalition is formed by the two players with highest* γ_i*. In the case of transfers, all possible 3-player coalitions are stable if* $n \leq 8$*, and if* $n \geq 9$ *no stable coalition comprises less than three players and* $f(n)$ *increases in* n.

12 Note that similar small coalitions are obtained for other strictly concave payoff functions as long as one does not assume Stackelberg leadership of signatories (see Finus 2003).

Uncertainty Case 3: No Transfers

$$E\left[m^{*FL}\right] = g(n) < 3 \quad \forall \gamma \quad and \quad n$$

Uncertainty Case 3: Transfers

$$E\left[m^{*FL}\right] = \begin{cases} 3 & if \quad n \le 4 \\ h(n) > 3 & if \quad n \ge 5 \end{cases}$$

where in the case of no transfers $g(n)$ *is a strictly increasing function with* $\lim_{n \to +\infty} g(n) = 3$. *In the case of transfers, all possible 3-player coalitions are stable if* $n \le 4$, *and if* $n \ge 5$ *no stable stable coalition comprises less than three players and* $h(n)$ *increases in* n.

In case 2 without transfers, the expected coalition size falls short under full learning compared to those under partial and no learning. This also applies to case 3 without transfers, although no closed form solution exists for full learning.

It is interesting to observe that with transfers asymmetry may no longer be an obstacle for forming large coalitions but may even be conducive. Due to the assumption about the distribution of the variables Γ_i, the degree of asymmetry among players (measured as the variance of the elements of the vector Γ) increases with the number of players n. Hence, above a threshold, $n \ge 9$ in case 2 and $n \ge 5$ in case 3, larger coalitions can be stable than in the case of symmetric players. The intuition is the following.

Cooperation among some players compared to the non-cooperative status quo typically serves two purposes. First, internalizing an externality among coalition members by choosing higher abatement levels than under no cooperation. This is a benefit every coalition member enjoys and, in fact, also non-signatories. Second, equalizing marginal abatement costs across coalitions members and hence reaping the gains from cost-effectiveness. This is a benefit the coalition enjoys as a group but does not spread to non-signatories. The first benefit from cooperation also applies to symmetric players, though not the second one. Hence, the potentials aggregate gains from cooperation are higher among heterogeneous than among homogeneous coalitions members, including an exclusive component. However, these gains can only be enjoyed by using a transfer scheme that optimally mitigates free-rider incentives; otherwise larger fruits can be picked but because some members receive a too small share they do not participate in cultivating and harvesting them.

The main conclusion from Propositions 3 and 4 to be reminded for the subsequent analysis is that there is no difference in stability between partial and no learning. Hence, all difference in the final outcome must stem from the second stage, related to the information and strategic effect. This is also true for all three learning scenarios in uncertainty case 1. In uncertainty cases 2 and 3, there may be differences in the size of stable coalitions between full and partial learning, as well as between full and no learning, depending on the number of players n and whether there are transfers. Differences between full and partial learning are exclusively due to the first stage, related to the size of stable coalitions, and hence stem from the distributional effect from learning. Thus, the most complicated comparison is between full and no learning in cases 2 and 3, as all three effects make their mark.

5. Model Results

We now pull together the first and second stage of coalition formation to derive overall results. For the interpretation, we can draw on our extensive analysis of the information, strategic, and distributional effect, in section 4. Again, we take an ex-ante perspective for the comparison of the three learning scenarios, under the three uncertainty cases, in terms of expected abatement and payoff.

5.1 Case 1: Uncertainty about the Level of Benefits

In case 1, players are ex-ante and ex-post symmetric. Hence, under all three learning scenarios, stable coalitions comprise three players (Propositions 3 and 4). Consequently, what we know about total abatement (Proposition 1) and total payoffs (Proposition 2) from the second stage of coalition formation directly translates into Proposition 5 below.

Proposition 5: Outcome with Uncertainty about the Level of Benefits

In uncertainty case 1, under the full, partial, and no learning scenario, expected equilibrium total abatement levels and expected total payoffs are ranked as follows:

1)	*Total Abatement:*	$FL = PL = NL$	$\forall\, n \geq 2$
2)	*Total Payoff:*	$FL = PL > NL$	

Proof: Follows immediately from Propositions 1 to 4. **(Q.E.D.)**

Our results indicate that if there is only uncertainty about the level of the benefits from global abatement, "learning is good" in terms of payoffs. This result is in stark contrast to Kolstad (2007), and Kolstad and Ulph (2008, 2009). They find that though full learning leads to larger stable coalitions than no learning, expected total payoffs are smaller. For partial learning they find multiple equilibria for some parameter values, and conclude that the most likely equilibrium leads to lower membership and lower expected aggregate payoffs than full and no learning. Thus, in terms of payoffs, they suggest: $NL > FL > PL$. So what leads to this different result?

In their model with a linear payoff function, equilibrium abatement strategies in the second stage of coalition formation do not depend on the benefit parameter. Equilibrium choices are "abate" or "not abate" where the first is an equilibrium choice in the social optimum, and for signatories in sufficiently large coalitions, whereas the second is an equilibrium choice for non-signatories. Consequently, different from our model, there is neither an information nor a strategic effect in the second stage. Hence, in our framework, the conclusions would be: learning must be superior to no learning because of larger coalitions. Why is this different in their model?

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 does no longer pay to abate. This threshold depends on the parameter γ; the larger γ, the higher the benefits from cooperation and the less coalition members are needed to form a profitable coalition. Hence, the size of stable coalitions is decreasing in the benefit parameter γ and, as the authors show, this is a strictly convex function. Therefore, expected membership is higher under full than under no learning. In contrast, an increasing value of γ has two opposite effects on total payoffs. On the one hand, it implies higher payoffs because of higher benefits; on the other hand, it leads to lower payoffs because of lower membership. As the latter effect dominates, totals payoffs are strictly decreasing and concave in γ. Hence, expected welfare under learning is lower than under no learning.

5.2 Case 2: Uncertainty about the Distribution of Benefits

In case 2, players are ex-ante symmetric though ex-post asymmetric. For partial and no learning this does not affect coalition formation compared to case 1 because players take their membership decisions based on expected payoffs. This does not apply to full learning. Hence, transfers only matter for full learning.

Proposition 6: Outcome with Uncertainty about the Distribution of Benefits

In case 2, under the full, partial and no learning scenario, expected equilibrium total abatement levels and expected total payoffs are ranked as follows:

No Transfers

1) *Total Abatement:* $NL = PL > FL$

2) *Total Payoff:* $\begin{cases} NL = PL > FL & if \quad n = 3 \\ NL > PL > FL & if \quad n \geq 4 \end{cases}$

Transfers

1) *Total Abatement:* $\begin{cases} FL = PL = NL & if \quad n \leq 8 \\ FL > PL = NL & if \quad n \geq 9 \end{cases}$

2) *Total Payoff:*

$$\begin{cases} FL = PL = NL & if \quad n = 3 \\ NL > FL = PL & if \quad 4 \le n \le 8 \\ NL > FL > PL & if \quad n = 9 \\ FL > NL > PL & if \quad n \ge 10 \end{cases}$$

Proof: See Appendix 3. **(Q.E.D.)**

The superiority of no learning over partial learning entirely stems from the second stage of coalition formation (Propositions 1 and 2) as there is no difference in the size of stable coalitions (Proposition 3). As long as $n \ge 4$, the grand coalition is not stable and the strategic effect explains the difference in total payoffs. In the absence of transfers, the superiority of partial over full learning solely stems from differences in the size of stable coalitions (Propositions 3 and 4, case 2) as the second stage outcomes are the same (Propositions and 1 and 2). This is due to the distributional effect from learning.

Hence, if the level but not the distribution of the total benefits from cooperation is known, the more we learn, the worse is the final outcome. Thus, the veil of uncertainty mitigates the strategic behavior of players (i.e. NL>PL for total payoffs) and avoids low participation due to anticipated small shares of the gain from cooperation for some players (i.e. PL>FL for total payoffs and abatement levels).

However, once coalition members are ensured that they receive their "fair share" through an appropriate transfer scheme, the lack of sufficient participation under full learning can be avoided. In fact, heterogeneity becomes an asset, leading to larger coalitions. This distributional effect from learning explains the superiority of full over partial learning for $n \ge 9$. This effect also overrides the negative strategic effect from full learning compared to no learning for $n \ge 9$ in terms of global abatement, and for $n \ge 10$ in terms of global payoffs.

Thus, we generalize the negative result of Na and Shin (1998) about the role of learning by considering more than three players and including the intermediate case of partial learning in the analysis. Even more important, we qualify their conclusion by considering transfers and showing that this conclusion can be reversed, at least for full learning.

5.3 Case 3: Uncertainty about the Level and Distribution of Benefits

Like in case 2, in case 3 players are ex-ante symmetric but ex-post asymmetric. The average degree of asymmetry is positive, therefore larger than in case 1, but smaller than in case 2. Not surprisingly, this improves upon the relative performance of full learning compared to case 2, but weakens it compared to case 1, if there are no transfers. With transfers, like in case 2, heterogeneity becomes an asset under full learning.

Proposition 7: Outcome with Uncertainty about the Level and Distribution of Benefits

In case 3, under the full, partial, and no learning scenario, expected equilibrium total abatement levels and expected total payoffs are ranked as follows:

No Transfers

1) Total Abatement:

$$\begin{cases} FL < PL = NL & if \quad n < 29 \\ FL > PL = NL & if \quad n \geq 29 \end{cases}$$

2) Total Payoff:

$$\begin{cases} PL > NL > FL & if \quad n < 29 \\ PL > FL > NL & if \quad 29 \leq n < 32 \\ FL > PL > NL & if \quad n \geq 32 \end{cases}$$

Transfers

1) Total Abatement:

$$\begin{cases} FL = PL = NL & if \quad n = 3 \ \vee \ n = 4 \\ FL > PL = NL & if \quad n \geq 5 \end{cases}$$

2) Total Payoff:

$$\begin{cases} FL = PL > NL & if \quad n = 3 \ \vee \ n = 4 \\ FL > PL > NL & if \quad n \geq 5 \end{cases}$$

Proof: See Appendix 4. **(Q.E.D.)**

For a given coalition structure, expected total abatement levels are the same under all three learning scenarios (Proposition 1) and expected total payoffs under full and partial learning are identical but higher than under no learning (Proposition 2). Since there is no difference between partial and no learning in terms of coalition size, the equality in terms of expected total abatement and the superiority in terms of expected total payoffs follows immediately. Moreover, differences between partial and full learning must solely stem from different coalition sizes. For transfers, coalitions are never smaller but may be larger under full than under partial and no learning, which gives full learning an advantage. For no transfers, the distribution effect is more subtle as there are two dimensions. First, the expected coalition size under full learning $E\left[m^{*FL}\right]$ is always smaller than under partial and no learning. Second, the average benefit parameter of the members of stable coalitions is higher under full learning than under the other two learning scenarios, implying higher total abatement. As $E\left[m^{*FL}\right]$ increases with the number of players n, the first (negative) effect becomes smaller with increasing n and the latter (positive) effect dominates. It is for this reason that for $n \geq 29$ ($n \geq 32$) full learning generates higher expected total abatement (expected total payoffs) than partial learning. A similar explanation applies to explain the relation between full and no learning.

Taken together, in case 3 partial learning is always better than no learning and once transfers are introduce full learning ranks first. Only without transfers full learning may rank last but, compared to case 2, this does not happen always, as the degree of asymmetry is smaller. If we view case 3 as the most relevant case of actual negotiations because it captures uncertainty about the level and the distribution of the gains from cooperation, both relevant in climate change, then our results come to a far less negative conclusion than the previous literature. Even in a strategic context, more information must not necessarily be detrimental to the self-enforcing provision of a public good. However, the larger the uncertainty about the distribution of the gains from cooperation, the more important it is to hedge against free-riding through an appropriate transfer scheme.

6. Summary and Conclusions

This paper addressed the role of uncertainty and learning for the formation of self-enforcing international environmental agreements (SEIEAs). The central question was whether the veil of uncertainty aggravates or mitigates free-riding and on what this depends? The answer is not straightforward. Though more information certainly helps actors to make rational policy choices (information effect), they do not act in isolation: first because there are externalities across nations and second because not all nations adhere to the rules of environmental treaties. When signatories and non-signatories choose their optimal policy levels more information might turn out to be worse as they interact strategically and choices are mutually depended (strategic effect). The veil of uncertainty might also be helpful when it comes to commit to cooperation by joining an agreement when the gains from cooperation could be unevenly distributed (distribution effect). Knowing ex-ante the total size of the pie is advantageous but receiving confirmation that the individual slices of participants might be quite unequal may cause problems.

In our SEIEA-model these issues were systematically analyzed. One the one hand, we distinguished three learning scenarios. The benchmark cases of no and full learning, and the intermediate case of partial learning where countries have to take their membership decision under uncertainty before they learn the true parameters of their payoff function. On the other hand, we considered three uncertainty cases. All cases assume that if there is uncertainty, all players know as much or little about their own as well as their fellows' payoff function. Thus, uncertainty is symmetric. Two benchmark cases considered uncertainty either about the level or the distribution of the gains from cooperation whereas the intermediate case allowed for both.

Roughly speaking, the larger the uncertainty about the distribution compared to the level of the gains from cooperation, the stronger is the strategic and the distributional effect compared to the information effect from learning. The strategic effect can be negative with the outcome the more we learn the worse it is. The distributional effect from learning only affects full learning, as only then the distributional consequences when deciding about membership are known. The impact of this distributional effect from learning increases with the variance of the shares of the gains from cooperation. Without transfers, this effect is negative, allowing only small agreements to be stable. With transfers, this effect is positive, and heterogeneity becomes an asset. Overall our conclusions are twofold.

First, the negative conclusion about the role of learning in previous work by Kolstad (2007), Kolstad and Ulph (2008, 2009) and Na and Shin (1998), though certainly important, is less evident from our model when taking a broader view. Only if there is pure uncertainty about the distribution of the gains from cooperation can we confirm that learning is bad. As we have argued, this is most unlikely in the climate change context. Moreover, should the problem be virulent, it can be mitigated, fixed or even turned into an asset through an appropriate transfer scheme.

Second, it is this last comment which we think should receive particular attention. As in most economic problems involving externalities and heterogeneous agents, it is certainly also naïve to expect that the gains from cooperation will be evenly distributed ex-post. In order to secure the total gains from cooperation some safety valve has to be built in. We considered the most obvious one, namely the commitment to an ex-post transfer scheme. We have done so in a stylized way by assuming away any transaction cost associated with such redistribution. This is an optimistic view, but certainly a benchmark. With heterogeneity participants of an agreement enjoy not only the benefits from internalizing an externality from which non-members cannot be excluded, but they also enjoy the exclusive benefits from a cost-effective allocation of their coordination efforts. Clearly, this cost saving potential increases with diversity. Our transfer scheme could also be implemented indirectly through an emission permit trading scheme as it is currently in place in the European Union to meet Kyoto targets. Through the initial allocation of permits, our optimal transfer scheme could be replicated.

Despite we generalized some aspects of previous models, our model also shares some of their limitations. We pick only two which we believe are the most policy-relevant. First, we assumed that all players share the same beliefs which requires some agreement about the current scientific evidence. Similar, like in the literature on macroeconomic policies, there is currently no shared scientific evidence on climate change. Therefore, it would be interesting to analyze whether an evolvement to more similar views, e.g. through intensified international research collaborations, political dialogues, and institutional coordination through international bodies are conducive to the success of cooperation and on what this depends. Second, we did not consider uncertainty about the abatement cost parameters with possible asymmetric realizations. We expect that this would improve the effect of learning and would certainly provide further relief to the scientific community that more information does no harm to the global good.

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Appendix[13]

Appendix 1: Proof of Proposition 2

In the case of full and partial learning, using equilibrium abatement levels in (11) and inserting them into payoff functions in (8), gives ex-post payoffs:

$$\Pi^*_{i\in S}\left(S\right)=\gamma_i\left(m\sum_{\ell\in S}\gamma_\ell+\sum_{j\notin S}\gamma_j\right)-\frac{1}{2}\left(\sum_{\ell\in S}\gamma_\ell\right)^2$$

(I) $$\Pi^*_{j\notin S}\left(S\right)=\gamma_j\left(m\sum_{i\in S}\gamma_i+\sum_{k\notin S}\gamma_k\right)-\frac{1}{2}\left(\gamma_j\right)^2=\frac{1}{2}\left(\gamma_j\right)^2+m\gamma_j\sum_{i\in S}\gamma_i+\gamma_j\sum_{k\neq j\notin S}\gamma_k$$

$$\Pi^*\left(S\right)=\sum_{i\in S}\Pi^*_i\left(S\right)+\sum_{j\notin S}\Pi^*_j\left(S\right)=$$

$$\frac{1}{2}m\left(\sum_{i\in S}\gamma_i\right)^2+\left(\sum_{i\in S}\gamma_i\right)\left(\sum_{j\notin S}\gamma_j\right)\left(1+m\right)+\left(\sum_{j\notin S}\gamma_j\right)^2-\frac{1}{2}\sum_{j\notin S}\left(\gamma_j\right)^2$$

Taking expectations in order to compute ex-ante payoffs, gives:

Case 1:

$$E\left[\Pi^{FL=PL}_{i\in S}\left(S,\Gamma\right)\right]=\left(\frac{m^2}{2}-m+n\right)E\left[\Gamma_i^2\right]$$

(II) $$E\left[\Pi^{FL=PL}_{j\notin S}\left(S,\Gamma\right)\right]=\left(m^2+n-m-\frac{1}{2}\right)E\left[\Gamma_j^{\ 2}\right]$$

$$E\left[\Pi^{FL=PL}\left(S,\Gamma\right)\right]=\left(m^2\left(n-\frac{m}{2}\right)+\left(n-\frac{1}{2}\right)\left(n-m\right)\right)E\left[\Gamma_k^2\right]$$

13 For some proofs we only provide the intuition due to space limitations. Details are available upon request.

Case 2:

$$E\left[\Pi_{i\in S}^{FL=PL}\left(S,\Gamma\right)\right]=\frac{\left(n+1\right)\left(6n^2+\left(3m^2-5m+4\right)n+2m^2-4m\right)}{24}$$

(III) $$E\left[\Pi_{j\notin S}^{FL=PL}\left(S,\Gamma\right)\right]=\frac{\left(n+1\right)\left[3n^2+\left(3m^2-3m+1\right)n+2m^2-2m-1\right]}{12}$$

$$E\left[\Pi^{FL=PL}\left(S,\Gamma\right)\right]=\frac{\left(n+1\right)\left(6n^3+\left(6m^2-6m+2\right)n^2+\left(-3m^3+5m^2-2m-2\right)n-2m^3+2m\right)}{24}$$

Case 3:

$$E\left[\Pi_{i\in S}^{FL=PL}\left(S,\Gamma\right)\right]=\frac{\left(n+1\right)\left(n\left(3m^2-5m+6\right)+3m^2-7m\right)}{24}$$

(IV) $$E\left[\Pi_{j\notin S}^{FL=PL}\left(S,\Gamma\right)\right]=\frac{\left(n+1\right)\left(3n^2+n\left(3m^2-3m+2\right)+3m^2-3m-2\right)}{12}$$

$$E\left[\Pi^{FL=PL}\left(S,\Gamma\right)\right]=\frac{\left(n+1\right)\left(6n^3+\left(6m^2-6m+4\right)n^2+\left(-3m^3+7m^2-4m-4\right)n-3m^3-m^2+4m\right)}{24}$$

where in (II) $E\left[\Gamma_k^2\right]$ remains unspecified, as in case 1 no assumption about the distribution of the random variables Γ_k is necessary for the analysis.

In the no learning scenario, certainty equivalence holds. Thus, in the three uncertainty cases, payoffs are the same as those under certainty with $\gamma_k = E\left[\Gamma_k\right]\ \forall\, k\in N$:

$$E\left[\Pi_{i\in S}^{NL}\left(S,\Gamma\right)\right]=\left(\frac{m^2}{2}-m+n\right)\left(E\left[\Gamma_i\right]\right)^2$$

(V) $$E\left[\Pi_{j\notin S}^{NL}\left(S,\Gamma\right)\right]=\left(m^2-m+n-\frac{1}{2}\right)\left(E\left[\Gamma_j\right]\right)^2$$

$$E\left[\Pi^{NL}\left(S,\Gamma\right)\right]=\left(m^2\left(n-\frac{m}{2}\right)+\left(n-\frac{1}{2}\right)\left(n-m\right)\right)\left(E\left[\Gamma_k\right]\right)^2$$

where in cases 2 and 3 $E\left[\Gamma_k\right]=\left(n+1\right)/2$. In case 1, using (II) and (V), we find: $E\left[\Pi^{FL=PL}\left(S,\Gamma\right)\right]-E\left[\Pi^{NL}\left(S,\Gamma\right)\right]=Var\left[\Gamma_k\right]$, where $Var\left[\Gamma_k\right]>0$ by assumption. In case 2, using (III) and (V), we find $E\left[\Pi^{FL=PL}\left(S,\Gamma\right)\right]-E\left[\Pi^{NL}\left(S,\Gamma\right)\right]=$ $-\frac{\left(n+1\right)\left(n+m^2-1\right)\left(n-m\right)}{24}$ which is strictly negative for $n>m$, implying $S\neq N$, and zero if $n=m$, implying $S=N$, for all $m,n\in N$ and $m\leq n$. Finally, in case 3, using (IV) and (V), we find $E\left[\Pi^{FL=PL}\left(S,\Gamma\right)\right]-$ $E\left[\Pi^{NL}\left(S,\Gamma\right)\right]=\frac{\left(n^2-1\right)\left(n+m^2-m\right)}{24}$ which is strictly positive for all $m,n\in N$ and $m\leq n$.

Appendix 2: Proof of Propositions 3 and 4

Proposition 3: For partial learning we use expected payoffs in (II), (III) and (IV) for the three uncertainty cases, respectively, and apply definition (4) of internal and definition (5) of external stability which delivers the result. For no learning, we use expected payoffs (V) and again apply the definitions of internal and external stability. For both learning scenarios, it is straightforward to see that the stable coalition of three players Pareto-dominates the singleton coalition.

Proposition 4: For full learning, in case 1, the equilibrium coalition size immediately follows from symmetry. For no transfers, in cases 2 and 3, we note that there are γ-vectors with asymmetric entries. Consequently, $E[m^{*FL}]<3$, as it can be shown, using payoffs in (I) and the definition of internal stability in (4), that for all non-symmetric γ-vectors no coalition of three or more players is internally stable. For case 2, the particular result that only the single coalition is stable if $n=3$ and comprises the two players with the highest γ_i if $n\geq 4$ is also immediately derived by using (I) and (4). As for case 3 no closed form solution exists, we consider all possible γ-vectors and compute the average size of Pareto-undominated coalitions. Repeating this for different values of n gives $g(n)$, which is a strictly increasing function. This procedure was implemented through an algorithm programmed with the software package Matlab.

For transfers in cases 2 and 3, we first prove that all coalitions of three or less players are potentially internally stable using payoffs in (I) and the definition of potentially internal stability in (6). Given the relation between potential internal stability and external stability, it follows that all coalitions strictly smaller than 3 must be externally unstable and hence cannot be stable. Thus, $E[m^{*FL}] \geq 3$ follows. Now it suffices to show that potential internal stability is violated for all coalitions larger than three players if $n \leq 8$ in case 2 and if $n \leq 4$ in case 3 by considering all possible γ-vectors in cases 2 and 3, respectively, up to these thresholds (and hence $E[m^{*FL}] = 3$ follows). Above these thresholds, we show that there is at least one γ-vector of the form $(1,2,3,n)$ in case 2 and of form $(1,1,1,n)$ in case 3 for which potential internal stability holds. Since either these 4-player coalitions or larger coalitions are externally stable, we can conclude that $E[m^{*FL}] > 3$.

Appendix 3: Proof of Proposition 6

As a preparation for the following proofs note that in our setting a property holds, which we call "Global Efficiency from Cooperation" (GEC). It means that whenever a non-signatory k joins coalition S, such that the coalition size changes from m to $\hat{m} = m+1$ (hence $\sum_{i \in S} \gamma_i$ and $\sum_{j \notin S} \gamma_j$ become $\sum_{i \in S} \gamma_i + \gamma_k$ and $\sum_{j \notin S} \gamma_j - \gamma_k$), total abatement and total payoffs strictly increase. For partial and full learning this can be shown using (11) for total abatement and (I) for total payoffs (hence it also holds when taking expectations) and for no learning using (12) and (V), respectively.

The relations between partial and no learning in Proposition 6 follow directly from combining Propositions 1 and 3 for expected total abatement levels, and from Propositions 2 and 3 for expected total payoffs.

Comparing full and partial learning we note that second stage outcomes are the same (Propositions 1 and 2). Hence, we concentrate on first stage outcomes (Propositions 3 and 4). Consider first no transfers. If $n=3$, then $E\left[m^{*PL}\right]=3>1=E\left[m^{*FL}\right]$. Since expected total abatement is given in (12) (which is taking expectations over (11)) and the expected total payoff is given in (III), and both increase in m, the result immediately follows from property GEC. If $n\geq 4$, then $E\left[m^{*PL}\right]=3>2=E\left[m^{*FL}\right]$, but the 2-player coalition under full learning comprises the players with the highest benefit parameters, $n-1$ and n. Hence for full learning we insert this information into (11) and (I), and for partial learning we insert this information into (12) and (III). We get:

$$E\left[Q^{*PL}\right]=\frac{(n+6)(n+1)}{2}>\frac{n^2+5n-2}{2}=E\left[Q^{*FL}\right]$$

$$E\left[\Pi^{*PL}\right]=\frac{(n+1)\left(3n^3+19n^2-22n-24\right)}{12}>\frac{3n^4+16n^3-30n^2+29n-6}{12}=E\left[\Pi^{*FL}\right]$$

Consider now transfers. Up to $n\leq 8$, coalition sizes are the same (Propositions 3 and 4) and hence relations follow directly from Propositions 1 and 2. If $n\geq 9$, the expected coalition size under partial learning with three players is smaller than under full learning (Propositions 3 and 4) and hence relations follow from property GEC.

For the comparison between no and full learning, we can use the relations established above between no and partial learning, and between partial and full learning, except for expected total payoffs if $n\geq 9$. For the same coalition size, no learning would lead to higher payoffs than full learning (Proposition 2), but full learning leads to larger coalitions

(Propositions 3 and 4). In particular, the expected size of stable coalitions under full learning, $f(n) > 3$, increases in n. Hence, we compute the expected total payoff (based on (I)) over all Pareto-undominated stable coalitions under full learning by considering all possible γ-vectors for various $n \geq 9$ up to $n = 20$. This is compared to the expected total payoff under no learning using (V) and $E\left[m^{*NL}\right] = 3$; it is evident that the ranking $NL > FL$ changes to $FL > NL$ from $n \geq 10$. For large n, this is confirmed with the software package Matlab.

Appendix 4: Proof of Proposition 7

The relation between partial and no learning follows directly from the second stage (Propositions 1 and 2) as coalition sizes do not differ (Proposition 3). For transfers, the relation between full and partial learning follow directly from the first stage as second stage outcomes are the same. Up to $n \leq 4$ coalition sizes are the same, but if $n \geq 5$ full learning produces equal or larger stable coalitions than partial learning and hence the result follows from applying property GEC mentioned in Appendix 3. The relation between no and full learning follows from the relations between no and partial learning as well as partial and full learning, as established above. For no transfers, though $E\left[m^{*FL}\right] < 3 = E\left[m^{*PL=NL}\right]$, the identity of players matters under full learning. For partial and no learning expected total abatement is given by (12) and expected total payoffs by (IV) and (V), respectively, using $E\left[m^{*PL=NL}\right] = 3$. For full learning, using an algorithm programmed in Matlab, all possible γ-vectors for each n are generated, then all Pareto-undominated stable coalitions are selected, and finally the associated expected total abatement and total payoffs are computed, based on (11) and (I), respectively.