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Climate Cooperation under Heterogeneity Enforcement versus Technology Sharing

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Research Article

Keywords: International climate cooperation, repeated games, technology spillovers, climate policy, climate clubs, enforcement mechanisms

Posted Date: November 24th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11680073/v1

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Additional Declarations: No competing interests reported.

CLIMATE COOPERATION UNDER HETEROGENEITY
Enforcement versus Technology Sharing

Abstract

This contribution investigates under what policy and institutional conditions climate cooperation among heterogeneous sovereign countries can be preserved and sustained over time, in a repeated strategic environment with non-perfect compliance. We focus on the 19 sovereign members of the G20 - which account for about three-quarters of global greenhouse gas emissions - and the study examines whether alternative policy mechanisms can overcome free-riding incentives coming from the asymmetry between domestic costs and global benefits.

The analysis employs a *repeated-game framework* where countries choose between cooperation and defection during an infinite horizon. We compare two different institutional configurations, C0 and C1: i) C0, a benchmark regime combining sanctions (τ) and monetary transfers as incentives (ρ); and ii) C1, a technology-sharing regime reducing mitigation costs ex ante through a calibrated knowledge spillover (δ_club). The dynamic evaluation of these configurations is conducted via Monte Carlo simulations (T = 5,000, R = 300), assuming a three-period tolerance rule, and it provides the common basis for the cross-regime comparison.

Results suggest that without enforcement, cooperation collapses immediately. The technology-sharing regime achieves comparable cooperation rates (coop_rate_avg $\approx$ 0.985) and collapse probabilities (prob_collapse $\approx$ 0.030) with less than half the policy intensity (τ = 0.22 vs $\tau + \rho$ = 0.5) and no transfers.

The main contribution of our analysis is to show that policy design can matter as much as enforcement strength. *These findings support designing climate clubs as cooperative structures that reduce individual mitigation costs, and not as agreements based primarily on punishment or redistribution*.

Keywords: *International climate cooperation, repeated games, technology spillovers, climate policy, climate clubs, enforcement mechanisms*.

1. Introduction

Climate change mitigation is universally recognised as a global public good: benefits are global, while costs are domestic. This asymmetry generates free-riding incentives that make voluntary cooperation individually irrational in the absence of enforcement. The G20, accounting for about 77% of global emissions (**UNEP**, 2025), is the natural strategic sample for such a problem: if cooperation cannot be sustained within this group, effective global action becomes impossible.

This paper examines the potential G20 climate cooperation proposing a repeated-game framework in which countries interact strategically over an indefinite horizon. Each country is assigned a cost index (CO_2 intensity), a benefit index (avoided climate damages scaled by GDP and adjusted for vulnerability through ND-GAIN), and emissions weight (share of total G20 emissions).

The approach proposes two institutional configurations. The first (Case 0) is a benchmark enforcement regime in which there are two exogenous policy instruments, the sanctions (τ) and the incentives (ρ). The sanctions can be interpreted as external enforcement costs imposed on non-cooperative countries, or countries deviating from cooperation. On the other hand, the incentives represent positive transfers that reward participation in the cooperative arrangement. Nevertheless, as will become clear from the analysis of Case 0, the model does not specify how these transfers are financed or by whom, which raises an important institutional question about their credibility and feasibility in a real-world framework. The second configuration (Case 1) replaces any monetary transfer with a technology-sharing configuration, that reduces mitigation costs ex ante through a calibrated knowledge spillover (δ_club). C0 is evaluated under both a static incentive-compatibility criterion and a dynamic robustness criterion, while C1 is assessed under the dynamic criterion. The dynamic evaluation of both configurations provides the common basis for the cross-regime comparison.

For these reasons, the main research question of the paper is to investigate *"Under which policy and institutional configurations can climate cooperation among heterogeneous countries be sustained as a stable outcome in a repeated strategic environment with imperfect compliance?"*

The work combines a repeated-game framework with an environment characterised by heterogeneous players, and mainly contributes to the literature in three ways: i- it proposes a realistic tolerance-based enforcement mechanism in a repeated game, evaluating each configuration in order to test whether cooperation survives over time, under the enforcement mechanisms implemented in the model; ii- it compares two institutional configurations (Case 0 and Case 1) in order to understand how different policy architectures affect cooperation outcomes; in this respect, unlike earlier spillover-based coalition models focused on coalition formation, the present analysis takes G20 membership as given and asks whether technology sharing changes the enforcement required to sustain cooperation over repeated interaction. iii- lastly, we conduct a comprehensive robustness analysis which quantifies the policy-efficiency advantage of technology-sharing through a multidimensional dominance criterion and a break-even analysis.

2. Literature Review

Barrett (1994, 2003) proves that self-enforcing environmental agreements face participation constraints and compliance incentives, and that cooperation becomes difficult with numerous and heterogeneous countries. Moreover, the studies of **Botteon and Carraro** (1997) show that the stability of environmental agreements depends on asymmetries in emission-related benefits and environmental damages, and this justifies the country-specific calibration adopted in Section 4.
Repeated games can sustain cooperation if players are sufficiently patient (**Fudenberg & Maskin**, 1986), even with imperfect monitoring (**Green & Porter**, 1984) and under alternative information structures (**Abreu, Milgrom & Pearce**, 1991). From a different

perspective, **Weikard, Wangler and Freytag** (2015) show that minimum participation rules can allow free-riding, illustrating that tolerance affects coalition design. More recently, **Okada** (2023) shows that full cooperation can emerge in a dynamic climate negotiation game when countries are sufficiently patient. Building on these contributions, we consider that real-world cooperation may be affected by uncertainty and imperfect compliance, making enforcement mechanisms excessively fragile when a single-period deviation is sufficient to trigger punishment. The model therefore proposes a three-period tolerant approach, designed to reduce the influence of shocks or deviations that are not caused by the intentional behaviour of the players.

Nordhaus (2015) proposed climate clubs with penalties on non-members. The coalition stability literature (**Carraro & Siniscalco**, 1993; **D'Aspremont et al**., 1983) shows that self-enforcing coalitions face internal and external stability constraints, but can be enlarged with transfers. Also recent works have examined climate transfers as a policy instrument in international climate negotiations (e.g. **Zheng et al**., 2026).

Technology spillovers diffuse through trade and cooperation (**Popp**, 2011, 2019; **Glachant & Dechezleprêtre**, 2017) and generate path-dependent productivity gains (**Acemoglu et al**., 2012). A close antecedent is **Nagashima and Dellink** (2008), who examine how alternative technology-spillover mechanisms impact the stability of partial climate coalitions among heterogeneous regions. They find that spillovers can reduce abatement costs, and increase coalition payoffs, but do not substantially overcome the free-riding incentives limiting larger coalitions. Their analysis treats spillovers as exogenous and focuses on coalition formation and stability; here, instead, coalition membership is fixed to the G20 and the question is whether an empirically calibrated club-level spillover can reduce the enforcement intensity needed to keep cooperation on, over repeated interaction. Recent work also links clean-technology transfer to enforcement requirements in agreements between asymmetric countries (**Konishi, Nakada & Shibata**, 2024).

3. Theoretical Model

3.1 Players and strategic environment

The players of the model are the 19 sovereign member economies of the G20 used in the empirical calibration. The European Union is not included as a separate player; only individual sovereign states are considered, consistently with the data strategy described below.

Let $\mathcal{N} = \{1, ..., N\}$ denote the set of players, where $N = 19$. In each period t, country i chooses action $a_{it} \in \{C, D\}$, where C represents cooperation, meaning that the country undertakes the emission reduction efforts, and D stands for defection. In order to keep the tractability, the model does not consider the possibility of partial compliance, and therefore the intermediate levels of mitigation effort are not considered. This simplification allows to characterise the incentive compatibility conditions and enforcement thresholds across the two institutional configurations, while remaining consistent with the binary compliance structure commonly adopted in the repeated-game literature focusing on international environmental agreements.

3.2 Country heterogeneity

The model considers countries that differ significantly in their economic structures, energy systems, and exposure to climate risks. These differences imply that both the costs of mitigation and the benefits from global emission reductions vary across the entities. To capture this heterogeneity the simulation gives each country i two main indices: b_i and c_i, and introduces in the payoff of defection a country-specific emissions weight ω_i. The parameter b_i represents the benefit that every country obtains through global emission reductions. This element reflects the level at which a country benefits from a successful mitigation effort, considering factors such as the size of the economy and its vulnerability to climate damages.

The parameter c_i represents the cost index associated with mitigation. The countries with higher values of c_i have to face relatively higher costs when they implement the reduction of emissions, most of the time it is because their economies are more carbon-intensive or dependent on fossil fuels. The estimation of b_i and c_i will be provided below. The last element $\omega_i \in [0,1]$ stands for the relative emissions weight of country i with respect to the

group, based on its contribution to total baseline emissions E_i.

3.3 Stage-game payoffs

If country i cooperates, it has to face the cost of mitigation but benefits from global emission reductions. The payoff associated with cooperation is therefore defined as:

$$\pi_i^C = b_i - c_i + \rho$$

where ρ represents the incentive granted to cooperating countries, as introduced in Section 1 as a positive transfer that rewards participation in the cooperative arrangement. If a country defects, it does not face the cost of mitigation while still obtaining a benefit from the emission reductions undertaken by other countries. Let E_i denote the baseline CO_2 emissions of country i in the reference year of calibration, and let E_tot = ∑ E_j for j = 1, ..., N denote total group emissions, so that the country-specific emissions weight is defined as ω_i = E_i / E_tot. Assuming a linear damage function where the global benefit of mitigation increases in proportion to total avoided emissions, the part of the cooperative benefit still obtained after unilateral defection is exactly b_i(1 - ω_i). The benefit obtained from defection is therefore not symmetric across players, and country i obtains only the fraction (1 - ω_i) of its full potential cooperation benefit, so that:

$$\pi_i^D = b_i(1 - \omega_i) - \tau$$

The parameter τ, calibrated in the model considering different potential values, represents a punishment applied to countries that defect from cooperation, designed to decrease the attractiveness of deviating from climate commitments, as discussed in Section 1 and further elaborated in Section 6. This implies that the largest emitters have to face a dual strategic tension because on one hand they have a stronger incentive to deviate since they have higher mitigation costs, on the other hand their defection causes a greater reduction in global mitigation and therefore a larger private loss of the public-good benefit, which weakens that incentive to deviate. If the cooperative arrangement collapses and all countries revert to non-cooperative behaviour, the global mitigation effort disappears and no player receives the public-good benefit. All countries then incur the sanction τ permanently, so that the punishment payoff is simply:

$$\pi_i^P = -\tau$$

The punishment is assumed permanent for tractability and consistency with the simulation design, where intended actions are fixed ex ante.

3.4 Repeated interaction and enforcement

The interaction between players is repeated over infinite periods and the future payoffs are discounted by a common factor:

$$\beta = 0.98, \quad \beta \in (0,1)$$

This choice β = 0.98 corresponds to a 2% annual discount rate, consistent with the median expert estimate in Drupp et al. (2018). To capture non-compliance which is due to frictions or shocks, the model introduces stochastic deviations ε. Intended actions are determined once (at the start) and remain fixed. The result is that strategic cooperators want to collaborate in every period while strategic defectors never do it and that the stochastic deviations included in the simulation can affect only strategic cooperators, causing them to accidentally defect in a given period with probability ε. The trigger mechanism is therefore activated by the randomness element ε only in the configurations in which all countries are classified as strategic cooperators and there is not a deliberate defection.

3.5 Incentive compatibility

The possibility of cooperation depends on whether it produces a payoff that is at least as large as the one produced by unilateral defection. Let V_i^C denote the expected future payoff for player i when cooperation is maintained, while V_i^D denotes the one associated with its unilateral defection. Cooperation is therefore incentive-compatible for player i if:

$$V_i^C \geq V_i^D$$

To express this condition more compactly, define:

$$\Delta_i = V_i^C - V_i^D$$

so that cooperation is individually rational whenever:

$$\Delta_i \geq 0$$

In other words, countries with $\Delta_i \geq 0$ are the intended cooperators, while countries with $\Delta_i < 0$ are the

intended defectors. In the punishment phase, player i receives an expected payoff:

$$V_i^P = \frac{-\tau}{1-\beta}$$

Under unilateral defection, that is:

$$V_i^D = \pi_i^D + \beta V_i^P$$

In the presence of stochastic deviations, let p_noise = ε denote the per-country probability of an accidental defection in a given period, as introduced in Section 3.4; and let N be the number of countries in the model. The probability P_trigger that at least one observed defection happens in a given period becomes:

$$P_{\text{trigger}} = 1 - (1-\varepsilon)^N$$

The continuation value under cooperation is then (after algebraic manipulations):

$$V_i^C = \frac{\pi_i^C + \beta P_{\text{trigger}} V_i^P}{1 - \beta\left(1 - P_{\text{trigger}}\right)}$$

3.6 Evaluation of cooperation sustainability

The model evaluates the sustainability of cooperation with the use of two complementary criteria, a static and a dynamic one, that try to address different questions.

The *static criterion* asks if cooperation is individually rational for each country under a strict analytical benchmark, and this condition is evaluated using the closed-form expected payoff derived in the previous section. Although this is an analytical approximation, the three-period streak rule used in the dynamic framework is not incorporated into this approach, because doing it would require a state-dependent recursive structure that distinguishes between different stages of the streak and would make the model more difficult and complex to implement. The first baseline calibration, ε = 0.001 and N = 19, yields p_trigger ≈ 0.0187. The share of countries that have $\Delta_i \geq 0$ measures how broadly cooperation is individually rational under this conservative benchmark. At that point the procedure selects the configuration that maximizes that share_ic_ok, since if there is a higher share it means that more countries find it individually rational to cooperate under the given enforcement parameters. If more than one configuration achieves the same share, the rule selects the regime that minimizes the total policy distortion τ + ρ, reflecting a preference for achieving the best results with the lowest possible intervention.

Because this one-period trigger probability exceeds the punishment probability under the three-period rule, the static benchmark is deliberately conservative.

In the dynamic simulation, the starting behaviour of each country is still determined by the empirically calibrated incentive structure by looking at the sign of Δ_i. In this framework the punishment is not activated by a single adverse observation but it is triggered only after three consecutive periods in which at least one country is observed to defect. Under this criterion, the best regime is selected through a *lexicographic rule* applied to the Monte Carlo simulation outcomes across T = 5000 periods and R = 300 replications for every institutional configuration. In other words:

The lexicographic rule first minimizes prob_collapse within a 0.01 tolerance band, then maximizes coop_rate_avg, and finally minimizes policy distortion (τ + ρ in Case 0; τ in Case 1).

4. Estimation of costs and benefits

This section proposes an empirical calibration of the two specific parameters for each country that are considered in the model, the cost index c_i and the benefit index b_i. The empirical calibration is based on country-level data covering the period 2000–2023; and to ensure reliability and avoid potential distortions caused by incomplete data, only countries with at least 70 percent of the observations required for the construction of the indicators are included. The cost index is derived from average CO_2 intensity relative to GDP over the full panel period 2000–2023. The benefit index, by contrast, is not averaged over the full period but is anchored to the common reference year 2023, combining avoided climate damages scaled by GDP with a country-specific vulnerability adjustment based on the ND-GAIN index (Notre Dame Global Adaptation Initiative, 2023).

4.1 Economic valuation of emission reductions

In climate economics the most widespread measure that is used for this purpose is the Social Cost of Carbon (SCC) that represents the monetary value of the net harm to society caused by emitting an additional metric ton of CO_2 into the atmosphere in a given year. Because the benefit index b_i will be normalized across countries as described in Section 4.3, the ranking order of the countries is preserved under any proportional rescaling of the SCC, and the qualitative incentive structure of the model is therefore robust to the choice of SCC value.

Using the EPA (2023) estimate at a 2 percent discount rate, we set the 2023 SCC to USD 204 per metric ton of CO_2.

The economic benefits associated with emission reductions can be therefore computed as a function of both the level of the reduction and the initial level of emissions. Let E_i be the baseline CO_2 emissions of country i in the reference year 2023, and let r be the uniform abatement rate (r_abatement) applied to all countries. The quantity of avoided emissions is expressed as:

$$\Delta E_i = r \times E_i$$

Two modeling assumptions behind this formulation should be made explicit. First, the abatement rate r is assumed to be the same in all countries but, in reality, heterogeneous mitigation costs would imply different optimal reduction levels for different players. Imposing a uniform r is necessary to keep tractability in the simulation environment, and it is consistent with the focus of the model on the strategic conditions for cooperation, rather than on the optimal design of individual emission reduction pathways. Second, baseline emissions are kept fixed at their 2023 level throughout the analysis. The value of r_abatement adopted in this model is 4 percent per year, which represents a plausible and moderate mitigation effort consistent with the annual emission reductions implied by decarbonization pathways discussed in the recent climate policy literature.[1]

The gross monetary benefit for country i is obtained by multiplying its avoided emissions by the SCC:

$$\text{benefit_usd}_i = SCC \times \Delta E_i$$

Substituting the expression for avoided emissions yields:

$$\text{benefit_usd}_i = SCC \times r \times E_i$$

However, the model assumes that climate damages are not distributed uniformly across countries, since differences in geographical exposure, economic structure, and adaptive capacity imply that the benefits from emission reductions vary significantly across regions. To capture this cross-country heterogeneity, the monetary benefit is first scaled by each country's baseline GDP for the year 2023:

$$\text{benefit_ratio}_i = \frac{\text{benefit_usd}_i}{GDP_i}$$

The scaled benefit is then adjusted using a country-specific climate vulnerability factor based on the ND-GAIN vulnerability index, rescaled relative to the sample mean. Let v_i denote the vulnerability index for country i and $\bar{v}$ the sample mean, the normalized vulnerability factor is defined as:

$$w_i^{\text{norm}} = \frac{v_i}{\bar{v}}$$

The vulnerability-adjusted GDP-scaled benefit measure is therefore:

$$\text{benefit_ratio_weighted}_i = \text{benefit_ratio}_i \times w_i^{\text{norm}}$$

At that point the benefit_ratio weighted for the vulnerability factor is normalized obtaining the final benefit index b_i for each of the 19 G20 sovereign economies.

4.2 Cost of decarbonization

We use carbon intensity (CO_2/GDP) as a proxy for relative mitigation costs, which is a standard simplification, again because of tractability and comparability cross-country. Moreover, a high level of carbon intensity may also reflect historical production structures and energy systems, rather than only the current economic cost of reducing emissions.

In this formulation, the annual carbon intensity is defined as:

[1] r = 4% is consistent with the UNEP (2024) 2°C trajectory and the IPCC (2022) mitigation pathways.

$$\text{intensity}_{it} = \frac{E_{it}}{GDP_{it}}$$

where E_{it} denotes the annual carbon dioxide emissions and GDP_{it} is the gross domestic product of country i in year t. Let $\bar{I}$_i denote the average carbon intensity of country i over the sample period, defined as the average of intensity_{it} for t from 2000 to 2023. Since the purpose of the model is to capture relative differences in mitigation costs across countries, the country-specific average carbon intensity $\bar{I}$_i is then min–max normalized to obtain the cost index c_i, as it will be discussed in Section 4.3. For the purpose of the simulations in Section 5, countries are classified into two groups based on their position with respect to the sample median of c_i. Countries with a c_i strictly above the median are classified as high-cost (type H), while countries at or below the median are classified as low-cost ones (type L).

4.3 Normalization of cost and benefit components

The values of mitigation costs and climate benefits depend on variables expressed in different units and magnitudes, including emissions, economic output, and climate vulnerability. To address this issue, each raw measure is rescaled to the unit interval [0,1] by applying a linear normalization based on the sample minimum and maximum, so that the country with the lowest value receives a score of zero and the one with the highest receives a score of one. Let X_i denote a generic variable representing either the cost or benefit component for country i (either the benefit_ratio_weighted $\tilde{B}_i$ or the country-specific average carbon intensity $\bar{I}_i$). The normalized value is defined as:

$$X_i^{\text{norm}} = \frac{X_i - \min_j X_j}{\max_j X_j - \min_j X_j}$$

where X_i denotes the raw value of either the benefit_ratio_weighted $\tilde{B}_i$ or the country-specific average carbon intensity $\bar{I}_i$ measure for country i, and the minimum and maximum are taken over the full cross-section of G20 countries j = 1, ..., N. Formally, the cost index is defined as:

$$c_i = \frac{\bar{I}_i - \min_j \bar{I}_j}{\max_j \bar{I}_j - \min_j \bar{I}_j}$$

and the benefit index as:

$$b_i = \frac{\tilde{B}_i - \min_j \tilde{B}_j}{\max_j \tilde{B}_j - \min_j \tilde{B}_j}$$

where $\bar{I}$_i is the average CO_2 intensity of country i (2000–2023), $\tilde{B}$_i is the vulnerability-adjusted benefit ratio (Section 4.1), and j indexes the 19 G20 economies.

5. Institutional Configurations and Simulation Results

The present section analyses the results of the simulation for the two institutional configurations. C0 is evaluated under both criteria defined in Section 3.6, while C1 is assessed under the dynamic criterion, and the final part of the section develops the cross-regime comparison and robustness analysis, providing the basis for the policy discussion in Section 6.

5.1 Case 0 – Benchmark enforcement: exogenous sanctions τ and incentives ρ

5.1.1 Motivation and mechanism: benchmark with exogenous τ and ρ

The first case presents τ and ρ as exogenous policy instruments. Although this benchmark is analytically useful to identify the combinations of τ and ρ to sustain cooperation, it leaves open the question of how the incentive component could be financed in the real world (a question addressed in Case 1). In this base case of the model, the cooperation yields the following cooperative payoff to every country:

$$\pi_i^C = b_i - c_i + \rho$$

If one of them deviates from cooperation it doesn't face the mitigation costs, but obtains only a fraction of the specific cooperation benefit that it would have obtained and incurs in a sanction:

$$\pi_i^D = b_i(1 - \omega_i) - \tau$$

As discussed in Section 3.3, once the cooperative arrangement collapses all countries enter the punishment phase and incur the sanction τ permanently:

$$\pi_i^P = -\tau$$

In order to evaluate the performance of different enforcement possibilities, the model explores a grid of policy parameters defined by alternative combinations of sanctions $\tau \in \{0, 0.05, 0.10, 0.20, 0.30\}$ and incentives $\rho \in \{0, 0.05, 0.10, 0.20, 0.30\}$, that yield 25 policy configurations.

5.1.2 Results and regime selection

From the first simulation there are two main patterns that emerge. The first one is that the high-cost countries often play a main role in early deviation and are the ones that cause trigger events, particularly in configurations where there are weak sanctions and incentives to stabilize cooperation. Second, when there is absence of both sanctions and incentives (in the baseline scenario) cooperation collapses almost immediately. In the absence of enforcement, collapse is immediate (trigger_time_mean = 3, prob_collapse = 1). Sanctions-only and incentives-only also lead to immediate collapse. Conversely, the situation changes when it is considered a combination of sanctions and incentives (club-mix regimes). However, robust performance is not a general property of all mixed regimes; only a small subset of sanction–incentive combinations is capable of preventing early collapse and sustaining cooperation over a long-term horizon.

Following the lexicographic selection rule that was defined in Section 3.6, the best-performing dynamic configuration is with $\tau = 0.2$ and $\rho = 0.3$. Under this mix of interventions, the average cooperation rate (coop_rate_avg) reaches approximately 0.985 (the average share of countries choosing to cooperate in each period, averaged over T = 5,000 periods and R = 300 Monte Carlo replications) and the probability that cooperation collapses is only about 0.033, so that a permanent breakdown occurs in just 3 percent of Monte Carlo replications.

On the other hand, the study also analyses a static selection criterion which, for each configuration (τ, ρ), computes the share of the countries that respect the incentive compatibility condition $\Delta_i \geq 0$ under the closed-form continuation values derived in Section 3.5 (share_ic_ok), and then applies the static selection rule defined in Section 3.6 to identify the best-performing configuration. That static procedure identifies a different regime from the one selected by the dynamic rule (τ, ρ) = (0.2, 0.3), selecting (τ, ρ) = (0.1, 0.3) which is sufficient to have share_ic_ok = 1. There is evidence that satisfying all incentive constraints in the analytical benchmark does not necessarily produce the same result as the long-run dynamic criterion, and this shows that the two criteria capture different dimensions of stability.

Case 0 therefore leaves a key institutional problem unresolved: ρ is an exogenous transfer with no specified financing mechanism. Case 1 addresses this by replacing transfers with cost-reducing technology sharing.

5.2 Case 1 – Technology-sharing agreement: cost-reducing spillovers

5.2.1 Motivation and mechanism: replacing monetary incentives with cost-reducing spillovers

The technology-sharing regime tries to solve the fundamental limitation of the previous configuration since it reduces the private cost of participation directly without attempting to reward or to push cooperation through financial transfers. This new mechanism is represented by a club-level technology spillover parameter δ_club defined as the fraction of mitigation costs which can be avoided with the technological knowledge shared in the cooperative arrangement. This spillover is not imposed exogenously, but it is calibrated through a club-level knowledge-pool measure derived from the R&D capacity of the participating economies. In this sense, δ_club is a common club-level parameter that does not reflect a subsidy that is country-specific, but a collective technological advantage applied uniformly to all cooperating countries. The cooperative payoff therefore becomes:

$$\pi_i^C = b_i - c_i(1 - \delta_{\text{club}})$$

while the defection and punishment payoffs in the long term maintain the structure used in the previous case.[2] The proportional cost reduction δ_club applies only to the countries that decide to cooperate since the ones that defect do not gain access to the shared

[2] The proportional cost reduction (about 15% here, see below) captured by δ_club assumes that the technological benefit scales linearly with the country's baseline mitigation cost. This simplification is common in reduced-form spillover models and is adopted for tractability. It will not affect the qualitative conclusion about break-even δ*.

technological pool and therefore continue to face the full baseline mitigation cost without any kind of reduction. What is important here is that this mechanism does not require any financial transfer across countries, being a configuration that addresses the cooperation problem by modifying its cost structure.

5.2.2 Calibration of the spillover parameter δ_club

Using 2018–2023 World Bank R&D data (**World Bank**, 2023), the calibration constructs country-level R&D capacity K_i, defines global and G20 knowledge pools, adjusts the latter for concentration through an inverse-Herfindahl diversity factor D, and derives country-level spillover ratios; calibration details are reported in Appendix (Table A.1).

$$s_i^{\text{eff}} = \frac{K_{G20}^{\text{eff}} - K_i}{K_{\text{world}} - K_i}$$

The numerator here captures the club's technological capacity net of country i's own contribution K_i, while the denominator rescales it against the global knowledge base available outside that country. This exclusion is done in order to have a parameter that captures only the additional technological advantage that country i obtains from the pool contribution of the other G20 members. The spillover parameter is then computed as the cross-country mean:

$$\delta_{\text{club}} = \text{mean}_i\left(s_i^{\text{eff}}\right)$$

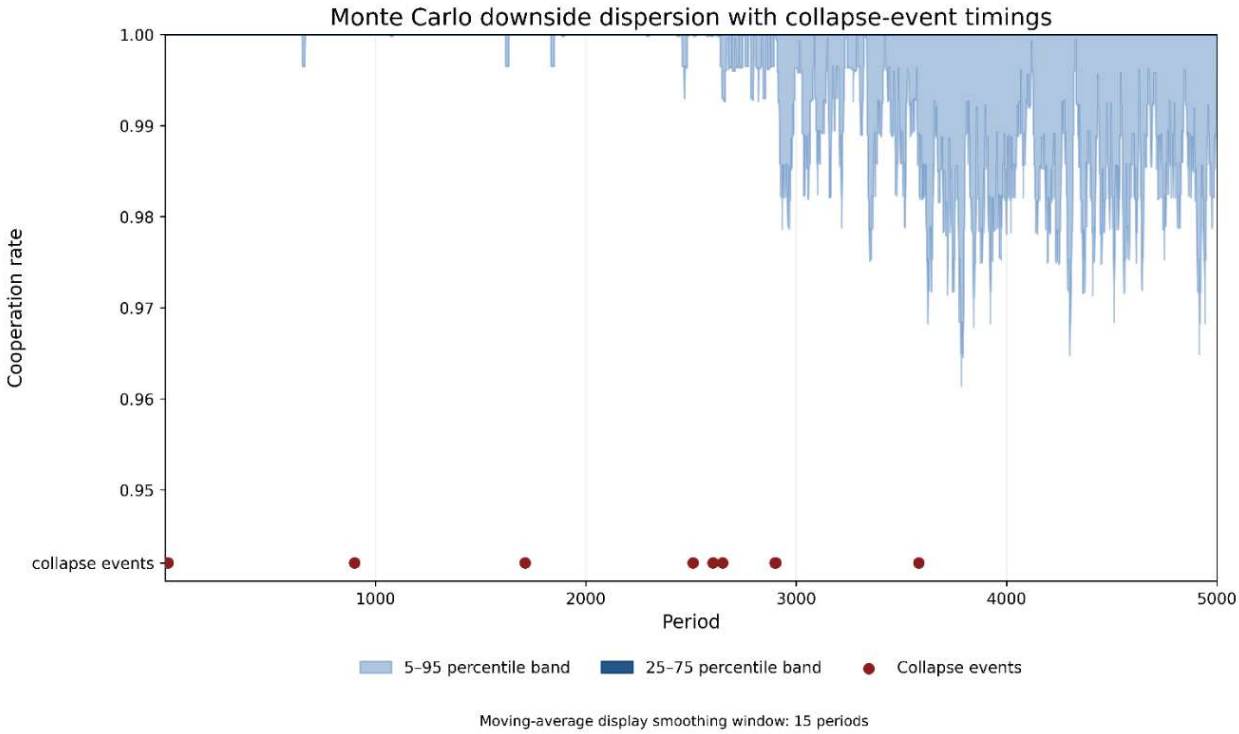
The resulting δ_club can be interpreted as the average cost-reducing technological gain that every cooperating G20 country obtains from club membership. In practical terms, this means that the effective mitigation cost of every country is reduced by about 15 percent for every country that cooperates, with bigger absolute reductions for the countries that have higher baseline mitigation costs (the ones most likely causing the collapse of the cooperation regime). In the current version of the model, δ_club must be understood as a simplified reduced-form measure of technological spillovers and not as the result of a fully structural innovation model. Instead, δ_club proxies the net effect of these mechanisms in a single normalized coefficient calibrated through the observed distribution of R&D capacity across countries.

Since δ_club is empirically calibrated and kept fixed across simulations, the analysis explores an expanded grid of sanction levels, $\tau \in \{0, 0.02, 0.04, 0.06, 0.08, 0.10, 0.12, 0.14, 0.16, 0.18, 0.20, 0.22, 0.24, 0.26, 0.28, 0.30\}$.

5.2.3 Simulation results and best regime

The results prove a threshold effect: for sanction levels below $\tau = 0.22$, cooperation collapses in all Monte Carlo replications (prob_collapse = 1, trigger_time_mean = 3), confirming that the technology spillover alone, without any enforcement support, is not enough to sustain cooperation. The Figure 1 below shows the evolution of the cooperation rate and collapse events.

Figure 1 - Evolution of the average cooperation rate in the technology-sharing regime



Evolution of the average cooperation rate over the simulation horizon (T = 5,000 periods) for the technology-sharing regime, under the base calibration. Results are based on R = 300 Monte Carlo replications. The coloured bands represent the 5–95 (light grey) and 25–75 (dark grey) percentile ranges of the cooperation rate across replications. Dots indicate the periods when the enforcement mechanism (Grim Trigger) is activated, leading to a permanent collapse.

As discussed in Section 3.6, only the dynamic criterion is considered in this configuration and applying the same lexicographic selection rule of Case 0, the procedure identifies that regime with $\tau = 0.22$ as the one with the optimal sanction level with a probability of collapse of 3 percent and an average cooperation rate of 0.9851. In practice, the normalized parameter τ is rescaled using the range of the vulnerability-adjusted benefit ratio across countries, so that the value becomes a fraction of national GDP. The resulting annual sanction corresponds to approximately 0.21 percent of national GDP (lower than the enforcement level required in Case 0, where the best dynamic configuration required a combined distortion of $\tau + \rho = 0.5$). This reduction reflects the structural advantage of the technology-sharing mechanism that lowers the private cost of mitigation through δ_club and reduces, in fact, the amount of explicit deterrence needed to make cooperation individually rational, addressing the cooperation problem ex ante rather than compensating for it ex post.

5.3 Cross-regime synthesis and strategic implications

5.3.1 Regime comparison

The best-performing configurations identified under the dynamic and static criteria are reported in Table 1 below. The optimal technology-sharing regime achieves an equivalent level of cooperation (coop_rate_avg ≈ 0.985) and a lower probability of collapse (prob_collapse ≈ 0.030) compared to Case 0, while requiring a level of policy intensity of $\tau = 0.22$ against $\tau + \rho = 0.5$ in Case 0 (less than half of the enforcement burden) and without relying on transfers whose financing remains unspecified.

Table 1 - Best-performing configurations under the static and dynamic criteria

Regime	Params	Performance	Intensity
Case 0 (dynamic)	τ=.20, ρ=.30	coop .985 / coll .033	.50
Case 0 (static)	τ=.10, ρ=.30	share_ic_ok=1	.40
Case 1 (dynamic)	τ=.22, δ=.15	coop .985 / coll .030	.22

Notes: Policy intensity is τ + ρ for Case 0 and τ for Case 1; δ_club is calibrated rather than policy-variable. Full parameter grids are reported in Appendix Tables A.2 and A.3.

5.4 Robustness Analysis

5.4.1 Motivation and scope

The baseline comparison favours technology sharing, but this conclusion could depend on the calibrated discount factor, stochastic noise, tolerance rule and spillover intensity. The robustness analysis tests the results by varying the discount factor, stochastic noise, tolerance rule and spillover intensity in both the following exercises (namely: preliminary and refined); Step 1 also varies the abatement rate, while the refined exercise varies benefit scaling instead.

In order to perform the check: the *first step* replicates the original binary comparison logic, testing whether the regime with the higher cooperation rate remains the same across parameter variations; the *second step* adopts a refined economic criterion: rather than asking which regime yields a higher cooperation rate, the question is whether technology-sharing achieves comparable or superior cooperation and stability with less policy intensity.

5.4.2 Step 1: Binary comparison (preliminary)

In Step 1, the 576-scenario grid varies β (0.95, 0.97, 0.98, 0.99), ε (0.001, 0.0025, 0.005, 0.01), trigger_streak (2, 3, 4), r_abatement (0.02, 0.04, 0.06), and delta_scaling (0.5, 0.75, 1.0, 1.25).

For each scenario, the optimal regime under the dynamic criterion is computed, and a binary winner (Case 0, Case 1, or Tie) is recorded, based on the average cooperation rate.

In the majority of scenarios, the cooperation rates of the two regimes are about the same (both near 0.985), and the winner is determined by Monte Carlo noise rather than by systematic differences. The binary comparison therefore fails to discriminate between the two institutional configurations in a statistically meaningful way.

5.4.3 Refined criterion: multidimensional dominance and policy efficiency

A refined criterion is adopted then, based on three simultaneous conditions. Let τ and ρ denote the sanction and the incentive parameter of the benchmark regime, so that the policy intensity of Case 0 is defined as: Policy_0 = τ + ρ.
For the technology-sharing regime, the policy intensity is simply: Policy_1 = τ , since no monetary incentive is used.
Let $coop_1$ and $coop_0$ denote the average cooperation rates (coop_rate_avg) of Case 1 and Case 0, respectively; then:

1. **Cooperation condition**: $coop_1 \geq coop_0$ (Case 1 yields at least as much cooperation as Case 0)
2. **Stability condition**: $collapse_1 \leq collapse_0$ (Case 1 is at least as stable as Case 0)
3. **Efficiency condition**: Policy_1 ≤ Policy_0 (Case 1 requires no more policy intensity than Case 0)

Dominance requires all three conditions to hold in favour of one regime, with at least one strict inequality; an advantage requires at least two conditions, while the remaining cases are classified as trade-offs.

In addition to the dominance classification, we compute the policy saving of Case 1 relative to Case 0 for a common performance target:
Target: cooperation rate ≥ 0.90 AND collapse probability ≤ 0.05
- We find the *minimum policy* intensity required for Case 0 to meet the target: Policy_0*
- We find the *minimum policy intensity required for Case 1* to meet the same target: Policy_1*
- We compute the policy saving as: Policy Saving = Policy_0* - Policy_1*
- Finally, we compute the break-even δ*, defined as the minimum value of δ_club such that Case 1 can meet the performance target with policy intensity no greater than Policy_0*. If the break-even δ* is below the calibrated value of δ_club (0.148), this indicates

that the result would hold even if the technological spillover were smaller than our empirical estimate. The grid for this refined exercise – see the column *values* in Table 2 – comprises 576 scenarios (4 × 4 × 3 × 3 × 4), varying:

Table 2 - Parameter grid for the refined robustness

Parameter	Values	Description
β	0.95, 0.97, 0.98, 0.99	Discount factor (patience of countries)
ε	0.001, 0.0025, 0.005, 0.01	Stochastic noise (accidental defection probability)
trigger_streak	2, 3, 4	Number of consecutive bad periods required for punishment
benefit_scaling	0.75, 1.00, 1.25	Scale of the benefit index
delta_scaling	0.50, 0.75, 1.00, 1.25	Scale of the calibrated δ_club

Each scenario is evaluated with R = 300 Monte Carlo replications and T = 5,000 periods.

5.4.4 Results

The refined robustness exercise yields the following results (Table 3).

(A) Classification of scenarios:

Table 3 - Classification of scenarios under the refined robustness criterion

Classification	Nr. of scenarios	Percentage
Case 1 dominates	94	16.3%
Case 1 advantage	203	35.2%
Trade-off / equivalent	229	39.8%
Case 0 dominates	50	8.7%
Case 0 advantage	0	0%

Summary: In 297 out of 576 scenarios (51.6%), Case 1 either dominates or exhibits an advantage over Case 0. Case 0 dominates in 50 scenarios (8.7%), while 229 scenarios (39.8%) are classified as trade-off or equivalent.

(B) Policy saving:

Median policy saving: 0.14

(C) Break-even δ*:

Median break-even δ*: 0.07
Calibrated δ_club: 0.148

5.4.5 Interpretation

The refined robustness exercise confirms the central result of the paper. The policy saving is economically meaningful: a reduction of approximately 40–50% in enforcement burden. The break-even analysis shows that the result would hold even if the technological spillover were half as large as our empirical calibration suggests (e.g. in case of an overestimated calibrated δ_club, or if the concentration had been even higher).

While the binary comparison is unreliable, the refined criterion, based on dominance and policy efficiency, provides a more appropriate method to evaluate the robustness in this context.[3]

Figures A.4 and A.5 in the Appendix offer a graphical synopsis of regime comparison results by delta scaling and technology sharing, respectively.

6. Policy Implications

The two enforcement instruments operate through distinct mechanisms because the sanctions (τ) raise the cost of non-participation through deterrence, while the technology spillovers (δ_club) reduce the private cost of cooperation ex ante not focusing on the reward structure. The incentive parameter ρ, while analytically necessary in Case 0, is not carried forward to a full policy translation given the absence of a specified financing mechanism.

[3] We do not include r_abatement as a sensitivity parameter in the refined exercise because b_i is min-max normalised: multiplying all benefits by a common constant does not alter the normalised values or country ranking. Benefit_scaling instead varies the post-normalisation scale and therefore affects the incentive structure.

6.1 Enforcement and the policy meaning of sanctions

The best real-world example of τ is a conditional penalty imposed due to non-participation in a cooperative climate arrangement. In contemporary policy, the clearest example is the EU Carbon Border Adjustment Mechanism (CBAM) (**European Union**, 2023), an instrument that imposes monetary charges on carbon-intensive imports from countries that do not price carbon equivalently. A similar logic is behind proposals for trade-related climate measures within the G7 Climate Club framework, exclusion from preferential regulatory treatment, or suspension of market access linked to climate commitments. These instruments share the property that is captured formally by τ since they increase the relative cost for all the countries that remain outside the arrangement, without requiring a direct monetary transfer to cooperating countries. In the technology-sharing case, $\tau = 0.22$ is an annual sanction of approximately 0.21 percent of national GDP which can be seen as a moderate but credible enforcement burden.

6.2 Financial transfers

The parameter ρ reflects the logic of monetary transfers in climate cooperation that can be seen in policy terms as any instrument that increases the payoff from cooperation such as for instance climate finance flows directed to developing economies, the lending from multilateral development banks, and the side payments within cooperative agreements. Every one of these instruments shares the structural property of ρ in the model because it makes cooperation more attractive by increasing what a country obtains in exchange for cooperation, rather than by reducing the costs of mitigation. The main limitation of ρ as a policy instrument is institutional rather than analytical, because the model introduces it as an exogenous positive transfer but it is not able to specify who provides it or on what basis, and this feature makes it analytically tractable but institutionally problematic.

To let ρ create a genuine incentive, transfers cannot be symmetrically self-financed; they must be asymmetric and redistributive across countries.

6.3 Technology-sharing and cost-reducing cooperation

Technology-sharing operates through a mechanism that is different from sanctions or transfers, structurally: it makes cooperation cheaper by reducing the private cost of mitigation directly. The key policy implication is that technology cooperation must be exclusive to club members; if offered as an open public good, it loses its incentive properties and δ_club ceases to function as an enforcement instrument. Making the technology-sharing element conditional on participation is therefore a structural requirement for the cooperative arrangement to remain self-enforcing. These results are consistent with Nagashima and Dellink (2008), as they show that technology spillovers alone do not eliminate free-riding. *Our analysis adds that, once combined with credible enforcement, technology sharing can reduce the enforcement intensity required to sustain cooperation in a fixed heterogeneous coalition.*

7. Conclusion

7.1 Main results

The analysis reaches two main results. The first one is that voluntary climate cooperation is not self-enforcing in the absence of institutional support because when no enforcement instrument is present, the cooperative arrangement collapses immediately in all simulations, confirming that climate mitigation can be considered as a global public good for which voluntary action alone is not enough. The second main result is that even though the monetary incentive support is analytically necessary in Case 0, it seems to be institutionally incomplete without a specified and credible financing mechanism. Consequently, the technology-sharing regime of Case 1 becomes a possible solution to address the previous problem since it outperforms the benchmark: it reduces the mitigation costs by approximately 15 percent and it sustains cooperation with a $coop_rate_avg$ of 0.9851 and a $prob_collapse$ of 3 percent. These results are similar to the ones obtained by the best combination of Case 0, but they are achieved with less than half of the policy intensity ($\tau = 0.22$ vs $\tau + \rho = 0.5$). The main policy contribution of the paper is therefore not only to identify a successful configuration, but to show that

the type of institutional support determines whether cooperation is structurally robust and feasible.

Across 576 scenarios varying the discount factor, stochastic noise, tolerance rule, benefit scale, and spillover intensity, technology-sharing dominates or exhibits an advantage in 297 scenarios (51.6%), while Case 0 dominates in 50 scenarios (8.7%) and the remaining 229 scenarios (39.8%) are classified as trade-off or equivalent. The median policy saving is 0.14, and the break-even δ^* is 0.07, below the calibrated value indeed.

The difference in the results under the two criteria demonstrates that the regime that satisfies all incentive constraints is not necessarily the one that performs better under the dynamic criterion, as shown by the different best choices of Cases 0 ($\tau = 0.1$, $\rho = 0.3$) static vs ($\tau = 0.2$, $\rho = 0.3$) dynamic.

The paper demonstrates that technology-sharing is a more efficient policy instrument because it addresses the cost structure directly and reduces the private cost of mitigation for all countries, including those ones that would otherwise have no incentive to cooperate. In this sense, our work supports the view that climate clubs should be designed as cooperative structures that reduce the individual costs, rather than as agreements based only on punishment or redistribution.

7.2 Limitations and Directions for further Research

The analysis has some limitations, also deriving from the nature of the approach. First, the coalition membership is taken as given: the model fixes the cooperative group to the 19 G20 sovereign economies and does not consider the possibility of new entrances or exits.

Second, although the technology-sharing element is computed with the use of observed R&D data, it is not intended to provide a country-specific measure of technological spillovers; it is designed as an average, applied uniformly to all cooperating countries. As a consequence, δ_club should be interpreted as a simplified reduced-form proxy for the average technological gain generated within the club, rather than as a heterogeneous measure differentiated for every country.

Third, the data used to build the vulnerability-adjusted benefit index may also raise a limitation: the ND-GAIN vulnerability score aggregates 36 indicators across six life-supporting sectors (food, water, health, ecosystem services, human habitat, and infrastructure) into a unique measure. The uniform vulnerability adjustment applied in this contribution does not capture the heterogeneity in the nature of climate damages across economies.

As above mentioned, on the theoretical side the model restricts countries to binary choices (cooperate or defect), abstracting from partial compliance. The punishment phase is assumed to be permanent and irreversible; this abstracts from renegotiation. The abatement rate r is assumed uniform across all countries. Relatedly, the baseline emissions are kept fixed at their 2023 level over the entire simulation horizon, so that the model does not trace a decarbonization trajectory over time.

Future research could address the main limitations discussed above by exploring several extensions of the framework. An improved computation of δ_club could integrate real-world elements such as intellectual property regimes, heterogeneous absorption capacity, and sector-specific implementation barriers.

REFERENCES

Abreu, Dilip, Paul Milgrom, and David Pearce. 1991. "Information and Timing in Repeated Partnerships." Econometrica 59(6): 1713–1733.

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous. 2012. "The Environment and Directed Technical Change." American Economic Review 102(1): 131–166.

Barrett, Scott. 1994. "Self-Enforcing International Environmental Agreements." Oxford Economic Papers 46: 878–894.

Barrett, Scott. 2003. Environment and Statecraft: The Strategy of Environmental Treaty-Making. Oxford: Oxford University Press.

Botteon, Michele, and Carlo Carraro. 1997. "Burden-Sharing and Coalition Stability in Environmental Negotiations with Asymmetric Countries." In International Environmental Negotiations: Strategic Policy Issues, edited by Carlo Carraro, 26–55. Cheltenham: Edward Elgar.

Carraro, Carlo, and Domenico Siniscalco. 1993. "Strategies for the International Protection of the Environment." Journal of Public Economics 52(3): 309–328.

D'Aspremont, Claude, Alexis Jacquemin, Jean Jaskold Gabszewicz, and John A. Weymark. 1983. "On the Stability of Collusive Price Leadership." Canadian Journal of Economics 16(1): 17–25.

Drupp, Moritz A., Mark C. Freeman, Ben Groom, and Frikk Nesje. 2018. "Discounting Disentangled." American Economic Journal: Economic Policy 10(4): 109–134.

European Union. 2023. Regulation (EU) 2023/956 of the European Parliament and of the Council of 10 May 2023 Establishing a Carbon Border Adjustment Mechanism. Official Journal of the European Union, L 130/52.

Fudenberg, Drew, and Eric Maskin. 1986. "The Folk Theorem in Repeated Games with Discounting or with Incomplete Information." Econometrica 54(3): 533–554.

Glachant, Matthieu, and Antoine Dechezleprêtre. 2017. "What Role for Climate Negotiations on Technology Transfer?" Climate Policy 17(8): 962–981.

Green, Edward J., and Robert H. Porter. 1984. "Noncooperative Collusion under Imperfect Price Information." Econometrica 52(1): 87–100.

IPCC. 2022. Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press.

Konishi, Hideo, Minoru Nakada, and Akihisa Shibata. 2024. "Free Trade Agreements with Environmental Provisions between Asymmetric Countries: Transfer of Clean Technology and Enforcement." Environmental Economics and Policy Studies 26: 1–30. https://doi.org/10.1007/s10018-023-00374-0

Nagashima, Miyuki, and Rob Dellink. 2008. “Technology Spillovers and Stability of International Climate Coalitions.” International Environmental Agreements: Politics, Law and Economics 8: 343–365. https://doi.org/10.1007/s10784-008-9079-1

Nordhaus, William. 2015. "Climate Clubs: Overcoming Free-Riding in International Climate Policy." American Economic Review 105(4): 1339–1370.

Notre Dame Global Adaptation Initiative. 2023. ND-GAIN Country Index. University of Notre Dame.

Okada, Akira. 2023. "A Dynamic Climate Negotiation Game Achieving Full Cooperation." Journal of Economic Behavior & Organization 214: 657–669. https://doi.org/10.1016/j.jebo.2023.08.019

Popp, David. 2011. "International Technology Transfer, Climate Change, and the Clean Development Mechanism." Review of Environmental Economics and Policy 5(1): 131–152.

Popp, David. 2019. "Environmental Policy and Innovation: A Decade of Research." NBER Working Paper No. 25631.

UNEP. 2024. Emissions Gap Report 2024: No More Hot Air ... Please! Nairobi: United Nations Environment Programme.

UNEP. 2025. Emissions Gap Report 2025: Off Target – Continued Collective Inaction Puts Global Temperature Goal at Risk. Nairobi: United Nations Environment Programme.

EPA (U.S. Environmental Protection Agency). 2023. Report on the Social Cost of Greenhouse Gases: Estimates Incorporating Recent Scientific Advances. Washington, DC: U.S. Environmental Protection Agency.

Weikard, Hans-Peter, Leo Wangler, and Andreas Freytag. 2015. "Minimum Participation Rules with Heterogeneous Countries." Environmental and Resource Economics 62(4): 711–727.

World Bank. 2023. World Development Indicators. Washington, DC: World Bank.

Zheng, Guo-Liang, Hua Liao, Huiying Ye, Stefan Wrzaczek, and Yi-Ming Wei. 2026. "Climate Transfers for Mitigation and Adaptation under 1.5°C and 2.0°C Targets." Economic Analysis and Policy 92: 952–970. https://doi.org/10.1016/j.eap.2026.06.036.

APPENDIX

Table A.1. Calibration of δ_{club} (base year 2023)

Parameter	Value	Description
A. Data and sample		
Base year	2023	*Reference year for all calibration quantities*
B. Global and G20 R&D expenditures		
World R&D expenditure	USD 2.123×10^{12}	*Aggregate R&D expenditure across all countries (World Bank)*
G20 raw R&D expenditure	USD 1.857×10^{12}	*Sum of R&D expenditures of G20 economies*
G20 share of world R&D	0.8747	*G20 raw R&D expenditure / World R&D expenditure*
C. Concentration adjustment		
Effective contributors (N_{eff})	4.265	*Inverse Herfindahl index of G20 R&D shares:* $N_{eff} = 1/\sum s_i^2$
Diversity factor (D)	0.2245	*$D = N_{eff}$ / number of G20 members; adjusts for concentration*
Effective G20 pool	USD 4.168×10^{11}	*D × G20 raw R&D; accounts for diminishing diversification gains*
δ_{club} **(common spillover)**	**0.1482**	*Average share of effective G20 pool relative to non-club knowledge base, excluding own R&D. Implies ≈ 14.8% reduction in effective mitigation costs.*

***Notes**: R&D expenditure data are drawn from the World Bank (indicator GB.XPD.RSDV.GD.ZS) and converted into USD by multiplying each country's R&D-to-GDP ratio by nominal GDP. Values are averaged over the six-year window ending in the base year (2023). N_eff is the inverse Herfindahl–Hirschman index of G20 R&D expenditure shares, computed as $N_eff = 1 / \Sigma s_i^2$. The diversity factor is defined as D = N_eff/N, where N is the number of G20 members included in the calibration, and is used to adjust for concentration in the club knowledge base. The effective G20 pool is computed $KG20^{eff} = D$ x KG20. The spillover parameter δ_club is obtained as the cross-country mean of $(KG20^{eff} - K_i) / (K_world - K_i)$, where K_i denotes country i's own R&D expenditure. In the model, δ_club reduces the effective mitigation cost index proportionally for cooperating countries.*

Table A.2. Case 1: Technology-sharing regime

τ	δ_{club}	coop_rate_avg	prob_collapse	collapse_mean	trigger_time_mean
0	0.1482	3.784×10^{-4}	1	1	3
0.02	0.1482	4.731×10^{-4}	1	1	3
0.04	0.1482	5.362×10^{-4}	1	4	3
0.06	0.1482	5.366×10^{-4}	1	4	3
0.08	0.1482	5.365×10^{-4}	1	4	3
0.1	0.1482	5.364×10^{-4}	1	4	3
0.12	0.1482	5.676×10^{-4}	1	4	3
0.14	0.1482	5.675×10^{-4}	1	4	3
0.16	0.1482	5.676×10^{-4}	1	4	3
0.18	0.1482	5.680×10^{-4}	1	4	3
0.2	0.1482	5.680×10^{-4}	1	4	3
0.22	0.1482	0.9851	0.030	2672.667	2671.667
0.24	0.1482	0.9747	0.043	2195.846	2194.846
0.26	0.1482	0.9850	0.033	2890.900	2889.900
0.28	0.1482	0.9788	0.043	2672.231	2671.231
0.3	0.1482	0.9695	0.053	2233.938	2232.938

***Notes:** τ = sanction parameter; δ_club = common technology-sharing spillover parameter calibrated from G20 R&D expenditure data; coop_rate_avg = average cooperation rate over the full simulation horizon; prob_collapse = frequency of collapse episodes across Monte Carlo replications; collapse_mean = average time to collapse, conditional on collapse; trigger_time_mean = average time to the first trigger.*

Table A.3. Case 0: Full regime comparison result

τ	ρ	coop_rate_avg	coop_rate_pretrigger	coop_rate_H	regime
0	0	3.46×10^{-4}	0.578	0.666	baseline
0.05	0.05	5.36×10^{-4}	0.894	0.778	club_mix
0.05	0.1	5.36×10^{-4}	0.894	0.778	club_mix
0.05	0.2	5.68×10^{-4}	0.947	0.889	club_mix
0.05	0.3	5.68×10^{-4}	0.947	0.888	club_mix
0.1	0.05	5.36×10^{-4}	0.894	0.778	club_mix
0.1	0.1	5.36×10^{-4}	0.894	0.778	club_mix
0.1	0.2	5.68×10^{-4}	0.946	0.888	club_mix
0.1	0.3	0.984	0.999	0.999	club_mix
0.2	0.05	5.68×10^{-4}	0.947	0.888	club_mix
0.2	0.1	5.68×10^{-4}	0.946	0.888	club_mix
0.2	0.2	0.974	0.999	0.999	club_mix
0.2	0.3	0.985	0.999	0.999	club_mix
0.3	0.05	5.68×10^{-4}	0.946	0.887	club_mix
0.3	0.1	0.978	0.999	0.999	club_mix
0.3	0.2	0.970	0.999	0.999	club_mix
0.3	0.3	0.971	0.999	0.999	club_mix
0	0.05	5.05×10^{-4}	0.841	0.778	incentives_only
0	0.1	5.36×10^{-4}	0.894	0.778	incentives_only
0	0.2	5.36×10^{-4}	0.894	0.778	incentives_only
0	0.3	5.68×10^{-4}	0.946	0.888	incentives_only
0.05	0	5.05×10^{-4}	0.841	0.778	sanctions_only
0.1	0	5.36×10^{-4}	0.894	0.777	sanctions_only
0.2	0	5.36×10^{-4}	0.894	0.778	sanctions_only
0.3	0	5.68×10^{-4}	0.946	0.888	sanctions_only

τ	ρ	share_H_trigger	trigger_time	prob_collapse	collapse_mean	mean_share_H	regime
0	0	0.374	375	1	1	0.374	baseline
0.05	0.05	0.995	3	1	4.00	0.998	club_mix
0.05	0.1	0.994	3	1	4	0.998	club_mix
0.05	0.2	0.997	3	1	4	0.997	club_mix
0.05	0.3	0.995	3	1	4	0.997	club_mix
0.1	0.05	0.997	3	1	4	0.999	club_mix
0.1	0.1	0.994	3	1	4	0.993	club_mix
0.1	0.2	0.990	3	1	4	0.993	club_mix
0.1	0.3	0.554	2416.1	0.030	2417.1	0.438	club_mix
0.2	0.05	0.994	3	1	4	0.997	club_mix
0.2	0.1	0.990	3	1	4	0.998	club_mix
0.2	0.2	0.538	2056.4	0.043	2057.4	0.483	club_mix
0.2	0.3	0.667	2889.9	0.033	2890.9	0.472	club_mix
0.3	0.05	0.993	3	1	4	0.997	club_mix
0.3	0.1	0.564	2602	0.043	2603	0.447	club_mix
0.3	0.2	0.479	2232.9	0.053	2233.9	0.468	club_mix
0.3	0.3	0.483	2235.6	0.050	2236.6	0.507	club_mix
0	0.05	0.664	3	1	3.99	0.662	incentives_only
0	0.1	0.995	3	1	4.00	0.999	incentives_only
0	0.2	0.997	3	1	4	0.997	incentives_only
0	0.3	0.996	3	1	4	0.997	incentives_only
0.05	0	0.665	3	1	3.98	0.666	sanctions_only
0.1	0	0.997	3	1	4	0.999	sanctions_only
0.2	0	0.996	3	1	4	0.999	sanctions_only
0.3	0	0.993	3	1	4	0.993	sanctions_only

Notes: *τ = sanction parameter; ρ = incentive parameter; coop_rate_avg = average cooperation rate over the full simulation horizon; coop_rate_pretrigger = average cooperation rate before the first enforcement trigger; share_H_trigger = average share of high-cost countries among triggering defectors; trigger_time_mean = average time to the first trigger; prob_collapse = frequency of collapse episodes across Monte Carlo replications; collapse_mean = average time to collapse, conditional on collapse; mean_share_H_first = average share of high-cost countries among first-period defectors; regime = policy family (baseline, club_mix, incentives_only, sanctions_only).*

Figure A.4. Regime comparison result by delta scaling

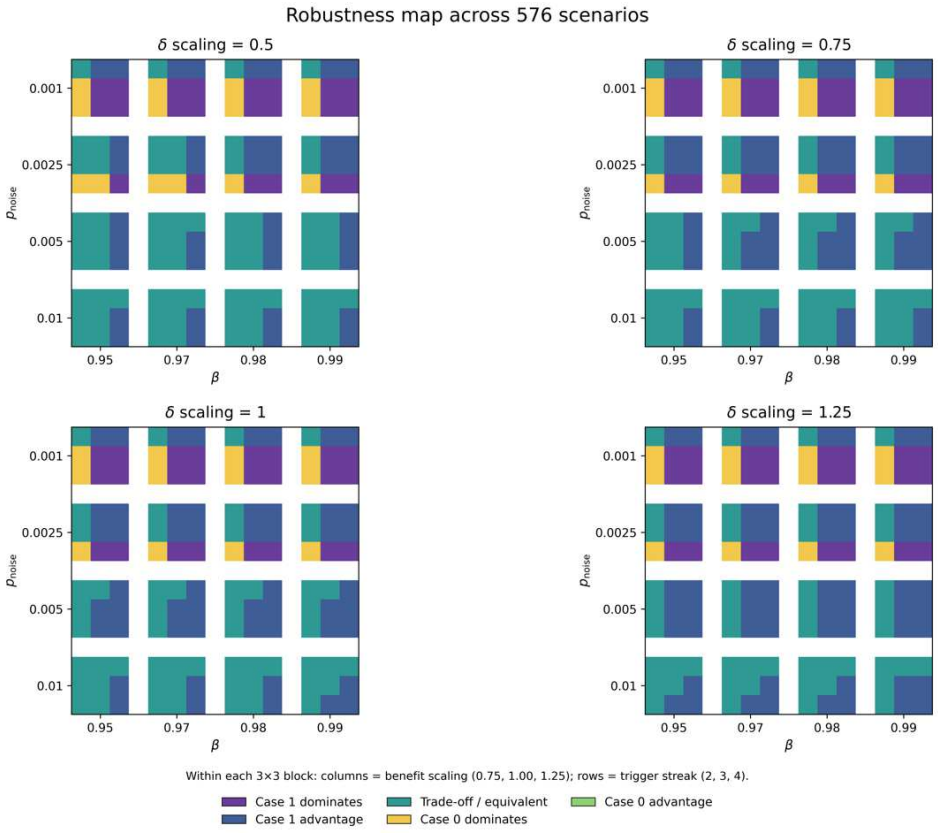
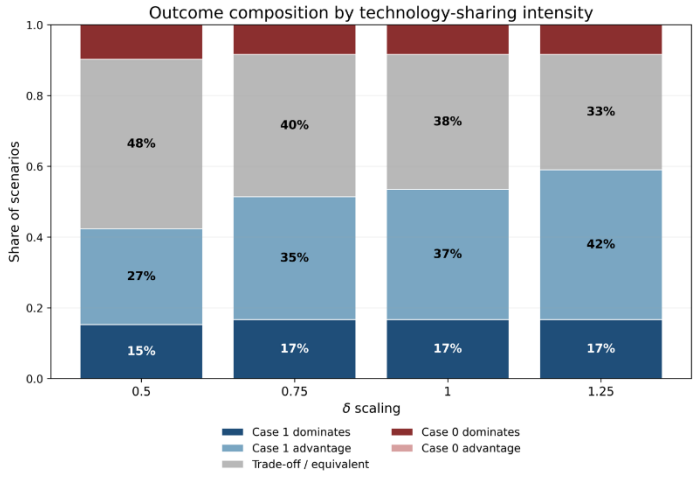


Figure A.5. Regime comparison result by technology sharing



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- APIEN.GHG.CO2.MT.CE.AR5DS2encsvv21052.csv
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- REPLICATIONcode.r
- vulnerability.csv