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Abstract

Facing possible disaster, countries can mitigate the risk of disaster or invest in adaptation to lower the impact of disaster. Contrary to a cooperative outcome, under non-cooperation the possibility to adapt can affect incentives to mitigate. We model this tradeoff in a transboundary pollution game where countries face an endogenous regime shift. We study a cooperative outcome and a non-cooperative Markov Perfect Nash Equilibrium. We find that mitigation efforts are reduced by the possibility to adapt, but this reduction is larger in a non-cooperative than a cooperative outcome. Furthermore, free-riding becomes more intense when either the impact of the disaster or the sensitivity of the hazard rate to the pollution stock increases. Finally, the gains from cooperation increase heavily when adaptation is possible.

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1 Introduction

Anthropogenic emissions put society at risk of crossing irreversible thresholds that inflict high economic and environmental damages (Scheffer, Carpenter, Foley, Folke, & Walker, 2001; Lenton et al., 2008; Rockström et al., 2009; Loriani et al., 2023). In anticipation of this possibility, countries can lower their emissions to mitigate the risk of crossing the thresholds or invest in adaptation to lower the impact of the welfare loss associated with crossing these thresholds: the mitigation-adaptation tradeoff (Crépin, Biggs, Polasky, Troell, & de Zeeuw, 2012; Zemel, 2015). In this paper, we show that the option to adapt significantly reduces incentives to mitigate if countries cannot agree to cooperate, contrary to literature that focuses on a single (representative) decision maker (e.g. Zemel (2015), van der Ploeg and de Zeeuw (2019)). This is due to the difference between mitigation and adaptation; the former has global effects and therefore suffers from free-riding, whereas the latter has local effects. We also show that we obtain similar qualitative results as Vardar and Zaccour (2018), while we employ a richer model that includes uncertainty and non-linear damages, a result not obvious beforehand.

The mitigation-adaptation tradeoff introduces tension between public and private responses to the economic consequences of crossing a climate threshold. In models with a single decision maker, e.g., Bréchet, Hritonenko, and Yatsenko (2013), Zemel (2015) and van der Ploeg and de Zeeuw (2019), there is no tension present since there is no difference between private and public goods. Single decision maker models advocate to have a mix between mitigation and adaptation policies, as also noted in studies that rely on Integrated Assessment Models (e.g., de Bruin et al. (2009); Bosello, Carraro, and De Cian (2010); Bahn, de Bruin, and Fertel (2019)), or by the IPCC reports (see Schumacher (2019) and references therein).

However, strategic considerations play a large role in the policy set out by countries; should a country mitigate, and therefore contribute to the public good, or should a country take local measures, i.e. adapt, and possibly free-ride on mitigation efforts of the other country? If countries can successfully coordinate cooperation, free-riding can be eliminated and the public good can be efficiently provided. Often, cooperation fails, and it is this situation in which adaptation affects incentives to mitigate.

In this paper, we study the mitigation-adaptation tradeoff in a model with uncertain environmental tipping and possible free-riding in mitigation. Environmental tipping is characterized by a sudden, irreversible regime shift from a state of high to one with low environmental quality. The timing of tipping is stochastic and determined by an endogenous hazard rate. Therefore, mitigation reduces likelihood of disaster, whereas adaptation reduces the impact of disaster. If countries do not cooperate, the two different policy instruments might not complement each other.

The mitigation-adaptation tradeoff comes in many facets. For instance, facing risk of loss of fisheries and associated loss of livestock, society can either lower this risk by lowering the pressure society puts on ecological systems (mitigation) or adapt and try to search for other forms of sustainable sources of production of fish that can replace a loss of fishery stock (adaptation) (Crépin et al., 2012). In the remainder of this paper, we consider the following setting. Consider two countries or regions that generate economic activity with the by-product of creating pollution, for instance carbon-dioxide (CO_2). Transboundary pollution drives up temperatures, and this in turn increases the likelihood of inducing regime shifts (MacDougall, 2016; Loriani et al., 2023). An example is the process of Artic Sea ice sheets melting, which can force an rise in sea levels and increases the likelihood of floods taking place. Two policy instruments can be used in response to possible disaster.[1] Mitigation is of the public kind; countries can reduce their emissions, which results in lower global pollution stock and therefore lower risk of disaster. Alternatively, countries can also resort to investments into local adaptation by for instance strengthening their dikes. Countries might resort to adaptation if they suspect that their efforts to mitigate the risk fall short due to non-cooperation, or when the risk cannot be fully eliminated.

We consider the mitigation-adaptation tradeoff in a differential pollution game (van der Ploeg & de Zeeuw, 1992; Dockner & Long, 1993). We add two model elements: non-linear dynamics in the form of a regime shift and investments into adaptive capital that lower the impact of the regime shift. Two countries share the problem of transboundary pollution, and face a tipping point of which the likelihood of occurrence is driven by the amount of pollution. Both countries have two options to respond to the looming tipping point; mitigation of emissions is a public good, whereas investment into adaptive capital is a private good.[2] We employ a hazard rate formulation for modelling the occurrence of the regime shift and solve for both a cooperative and non-cooperative outcome (the Markov Perfect Nash Equilibrium, or MPNE for short). The problem can be characterized by two sets of Hamilton-Jacobi-Bellman (HJB) equations, one that is used to determine the value function after the regime shift has taken place, and one that is used to determine the value function before the regime shift. We solve the resulting HJB equations pre-shift via collocation on sparse grids and sparse polynomial combinations. We compare outcomes to a situation where mitigation is the only possible response to disaster to assess how adaptation affects incentives to mitigate risk in response to disaster.

We find the following. First, due to the option to adapt, mitigation efforts are reduced more heavily in a non-cooperative than in a cooperative outcome. Second, free-riding increases heavily when the size of the shock or the sensitivity of the hazard rate with respect to pollution stock increases. Third, adaptation might complement mitigation in case of cooperation, but under non-cooperation it increases risk of disaster heavily. Finally, we provide a methodological contribution, as we are the first to characterize both cooperative and non-cooperative outcomes in a differential game with a regime shift that features more than one state variable.

This paper is structured as follows. Subsection 1.1 discusses related literature. Section 2 introduces the model and sections 3 and 4 solve for the social planner outcome and

[1] Another possible policy instrument is the use of geoengineering, i.e. artificially altering the climate. Meier and Traeger (2022) show that solar geoengineering can play a major role in incentives to reduce emissions, but it appears to be less costly than conventional measures such as mitigation and adaptation. However, given that its potential side-effects are highly ambiguous (see for instance Manoussi, Xepapadeas, and Emmerling (2018)), we do not consider it in our analysis.

[2] Although *knowledge* of adaptation of a country might spill over to other countries (Masoudi & Zaccour, 2018), *investments* into adaptation are purely local, and therefore allow us to differentiate between private and public goods.

MPNE, respectively. Section 5 discusses results and section 6 concludes.

1.1 Related Literature

The tradeoff between adaptation and mitigation in models with a single decision maker has been studied in Bréchet et al. (2013); Zemel (2015); van der Ploeg and de Zeeuw (2019). Bréchet et al. (2013) provide a growth model with linear environmental dynamics and analytically characterize the optimal policy. In a tractable dynamic model with an endogenous regime shift, Zemel (2015) provides analytical insights into the mechanisms that affect the joint decision on adaptation and mitigation. Interestingly, he finds that the possibility of adaptation allows for increases in the polluting good, which implies that scenarios with high pollution levels, in which there is a large hazard of a regime shift, are possibly optimal. Depending on the initial level of adaptive capital, it also might be optimal to delay investments into adaptive capital until the hazard is very high or not invest at all if the hazard rate is already too high. In van der Ploeg and de Zeeuw (2019), the authors analyze the mitigation-adaptation tradeoff in a Ramsey model with an endogenous regime shift. The authors find that investments into adaptive capital are increasing in pollution stock, and hence also in the probability of tipping.

The aforementioned papers feature a single decision maker and therefore do not consider the public good nature of mitigation, which loses two important points: there are no strategic incentives such as free-riding, and there is no tradeoff between local instruments and global instruments. We consider how non-cooperation between multiple countries affects the mitigation-adaptation tradeoff. For this, we build upon the seminal contributions by van der Ploeg and de Zeeuw (1992) and Dockner and Long (1993), who introduced a model that features multiple decision makers that share the problem of transboundary pollution and decide on emission levels over time, a model nowadays known as the transboundary pollution game.[3] This model has been extended and analyzed by different scholars to study how cooperation and non-cooperation affect incentives to reduce pollution (Kossioris, Plexousakis, Xepapadeas, de Zeeuw, & Mäler, 2008; Nkuiya, 2015; Benchekroun & Martín-Herrán, 2016; Vardar & Zaccour, 2018; El Ouardighi, Kogan, Gnecco, & Sanguineti, 2020; Wagener & de Zeeuw, 2021; Boucekkine, Ruan, & Zou, 2023).

We single several papers out. Nkuiya (2015) studies the precautionary effect under non-cooperation when mitigation is the only response to an endogenous regime shift, and finds that individual emissions decrease under linear Markovian strategies, and individual emissions either increase or decrease under non-linear Markovian strategies due to multiplicity of equilibria. Contrary to this work, we allow for adaptation to lower the welfare loss associated with the regime shift. Wagener and de Zeeuw (2021) consider a pollution game with non-linear dynamics and study whether stable partial cooperation in the Open-Loop Nash Equilibrium (OLNE) can avoid crossing a reversible tipping point. The authors find that the tipping point has a deterring effect; larger coalitions than in

[3] Static models with multiple decision makers include Benchekroun, Marrouch, and Ray Chaudhuri (2011); Masoudi and Zaccour (2018). The former studies the effect of increases in adaptation effectiveness on free-riding in environmental treaties and the latter studies how Research & Development (R&D) efforts into adaptation and spillovers from R&D efforts affect environmental treaties.

previous literature are found. However, tipping the system back might be ecologically possible but will require too high levels of cooperation to be socially possible. Boucekkine et al. (2023) study a non-linear pollution game with a deterministic, exogenous threshold of pollution. After this threshold is crossed, depreciation of the pollution stock vanishes and the game enters an irreversible regime, and the authors studies how this prospect affects free-riding when countries do not cooperate. We build on both Boucekkine et al. (2023) and Wagener and de Zeeuw (2021) by allowing for the timing of the regime shift to be stochastic, and we also study how adaptation changes incentives to mitigate.

Vardar and Zaccour (2018) study the strategic effect that adaptation has on mitigation in a pollution game under non-cooperation. The authors allow for investments in adaptive stock in order to reduce local damages. We build upon the paper by Vardar and Zaccour (2018) by allowing for non-linearities in both dynamics and damages, making a comparison between cooperation and non-cooperation and introducing uncertainty by means of a hazard rate approach.

2 Model

We study a two player differential game with a regime shift.[4] Time is continuous. The player (countries), indexed by $i = 1, 2$, obtain utility from consumption. However, each unit of consumption C_i increases global pollution stock P. Pollution harms social welfare. At a random moment in time, an irreversible regime shift occurs and there is an immediate loss of welfare due to incurred damages. We call this time of disaster T, and the occurrence is driven by a hazard rate that depends on the level of pollution stock:

$$H(P(t)) = \lim_{\Delta t \to 0} \frac{\Pr[t \leq T \leq t + \Delta t | T \geq t]}{\Delta t} = \lambda P^2(t) + \gamma.$$

Note that $H(P(t))\Delta t$ is approximately the probability that a regime shift from the first stage of the game to the second stage of the game takes place between time t and $t + \Delta t$, given that it has not taken place yet.[5] The special case $\lambda = 0$ results in a constant hazard rate of γ, which breaks the link between adaptation and mitigation. In this case, countries can only respond to the disaster by means of adaptation.[6] The focus of this paper is the interaction between mitigation, which reduces the risk of disaster, and adaptation, which lowers the impact of disaster. Hence, we assume that $\lambda > 0$.

Each country can invest before time T in local adaptive capital K_i, which lowers the impact of the catastrophe once it takes place. At time T a regime shift from a state with no climate disaster to a state with climate disaster takes place, and expectations need to be formed about the timing of this event. Welfare of country $i = 1, 2$, before the regime

[4] We could allow for an arbitrary amount of players, but this only adds in computational complexity.

[5] The cumulative distribution of T is simply given by $1 - e^{-\int_0^t H(P(s))\mathrm{d}s}$.

[6] One can show that if $\lambda = 0$, in both a cooperative and non-cooperative outcome, the resulting value functions will be additively separable in the state variables and the decision to invest in adaptation is independent of the level of pollution stock.

shift has taken place is defined as follows:

$$V_{iB}(P(0), K_i(0)) = \max_{\{C_i(t), I_i(t)\}_{t=0}^{\infty}} \Big\{ E_0 \Big[\int_0^T e^{-\rho t} \Big(U(C_i(t)) - F(I_i(t)) - D(P(t)) \Big) \mathrm{d}t + e^{-\rho T} V_{iA}(P(T), K_i(T)) \Big] \Big\}, \tag{1}$$

where $U(C_i)$ denotes utility from consumption, $F(I_i)$ denotes costs from investing in adaptive capital stock, D denotes damages from global pollution stock, E_0 denotes the expectation operator conditional on information at time 0; we form expectations as the time at which the regime shift takes place, T, is stochastic. Discounting takes place at constant rate ρ, which is identical across countries. $V_{iA}(P(T), K_i(T))$ acts as a 'scrap value'; it is the maximum level of welfare that can be obtained after the regime shift for a level of capital and pollution stock at time T:

$$V_{iA}(P(T), K_i(T)) = \max_{\{C_i(t)\}_{t=T}^{\infty}} \Big\{ \int_T^{\infty} e^{-\rho t} \Big[U(C_i) - D(P) - \Psi_i(K_i(T)) \Big] \mathrm{d}t \Big\}, \tag{2}$$

where V_{iA} is the value function of country i after the tipping point has occured and $\Psi_i(K_i)$ denotes damages that take place post-shift as a function of the level of adaptive capital stock. A country takes the level of adaptive capital built up upto time T as given in the second stage.

The global pollution stock is driven by consumption by both countries and evolves according to:

$$\dot{P}(t) = C_i(t) + C_j(t) - \delta P(t), P(0) = P_0. \tag{3}$$

where a fraction δ of the pollution stock dissipates. In the period before the regime shift, a second decision variable for each country is investment into a local adaptive capital stock. Investment is *proactive*: after the regime shift, there is no need to build up adaptive capital as impact of the regime shift has already materialized. The adaptive capital stock in each region i evolves according to:

$$\dot{K}_i(t) = I_i(t) - \delta_K K_i(t), K_i(0) = K_{i0},\ i = 1, 2, \tag{4}$$

where I_i denotes investment into adaptive capital K_i and δ_K denotes the rate at which adaptive capital depreciates. Adaptive capital decreases the damages in the second period. The main part of our functional forms are linear-quadratic, in line with previous literature on pollution control models (Dockner & Long, 1993; Nkuiya, 2015; Benchekroun & Martín-Herrán, 2016; El Ouardighi et al., 2020; Boucekkine et al., 2023). However, we introduce two types of non-linearities: regime shift dynamics and a non-linear function Ψ, the welfare loss associated with the regime shift. The utility function is given by:

$$U(C_i(t)) = a_i C_i(t) - \frac{b_i}{2} C_i(t)^2,\ i = 1, 2,$$

i.e. there are linear benefits and quadratic costs associated with consumption. Pollution damages are assumed to be quadratic:

$$D(P(t)) = dP(t)^2.$$

The investment function is given by:

$$F(I_i(t)) = \phi_i I_i(t) + \frac{\chi_i}{2} I_i(t)^2,\ i = 1, 2,$$

and we assume $I_i \geq 0, i = 1, 2$. If investments were purely quadratic, there would not be a possibility of a steady state in which there is no adaptive capital built up. Due to the linear term there is a possibility of no adaptation when costs are too high and benefits are too low.[7] Proactive investments into adaptation reduce the impact of the regime shift. Following Zemel (2015), the catastrophic damage function after the regime shift is given by:

$$\Psi_i(K_i(t)) = \frac{A_i Z_i}{Z_i + K_i(t)},\ i = 1, 2, \tag{5}$$

which has the properties $\Psi_i'(K_i) < 0, \Psi_i''(K_i) > 0$. In the case of no adaptation, the damages are maximal at A_i, and when adaptation stock reaches $K_i = Z_i$, damages equal $\Psi_i(Z_i) = \frac{A_i}{2}$; Z_i therefore measures the efficiency of adaptation. We assume that the size of the damages is known, but the timing of the regime shift is unknown. Finally, we assume that countries are symmetric.

We start by solving the social planner problem. After that, we work through the non-cooperative equilibrium, where we focus on Markovian strategies. These are strategies that are subgame perfect. The structure of the pollution game is as follows. At each moment in time, both countries decide simultaneously on their consumption and investment in adaptive capital. In response to future disaster, countries can decide on mitigation and adaptation. Lowering consumption is a mitigation strategy that has local welfare costs but global welfare gains, as the pollution stock is a public bad. Investments in adaptive capital result in both local costs and gains, as adaptive capital stock of country i does not directly benefit country j.[8]

The problem is solved via dynamic programming. At a random moment T, the regime shift occurs. This induces a multi-modal game structure where the transition between the two modes is governed by the endogenous hazard rate. The game then switches to the second stage, in which each country solves the after-shift problem defined by (2). We obtain a closed form solution for the value functions post-shift. We then turn to

[7] Dawid, Keoula, and Kort (2017) study investment into R&D in a differential game between two firms and consider a similar functional form. We follow their specification and assume that investments are non-negative: for example, a form of adaptation that improves water drainage to reduce the impact of a flood also does not easily allow for de-investments.

[8] Masoudi and Zaccour (2018) consider spillover of adaptation knowledge between countries. We abstract from such a formulation to fully isolate the interaction between public and private incentives in a cooperative and non-cooperative setting in response to climate disaster.

the pre-shift regime where welfare is maximized according to (1). As the pre-shift HJB equations are highly non-linear, we solve them numerically using collocation on sparse grids (Judd, 1998; Judd, Maliar, Maliar, & Valero, 2014).

In the following section, we study the social planner outcome. After that, we study the non-cooperative outcome. We then compare these outcomes with a respective cooperative or non-cooperative benchmark model where mitigation is the only instrument in response to climate disaster. This comparison allows us to assess how adaptation affects incentives to mitigate. We solve this model with the same methods we use to solve the model with adaptation and mitigation. The difference is that we set $K_i(t) = I_i(t) = 0, \forall i, t$, thus the size of the shock is fixed at $\Psi_i(0) = A_i$. The structure of the solution is similar but simplifies as there is only one state variable, pollution stock. Again, we solve the post-shift HJB equations analytically and resort to numerical methods to solve the pre-shift HJB equations. The full derivation can be found in Appendix A.2

3 Social Planner

In this section, we provide the social planner solution. We model adaptation to the consequences of a regime shift as local: in each country each individual benefits from this adaptation. An example is strengthening dikes in the Netherlands in response to rising sea levels, a process from which essentially the whole country benefits.[9]

We solve the social planner model backwards. After the regime shift has occured, the social planner problem reduces to finding the optimal paths for consumption, as investment is proactive and thus capital stock is fixed after the regime shift has taken place. This is similar to the cooperative scenario in Dockner and Long (1993), but with the addition of the damages due to the regime shift; for completeness, we provide the derivation. The social planner maximizes the sum of the individual social welfare functions:[10]

$$V_A^C = V_{1A} + V_{2A} = \max_{\{C_i, C_j\}_{t=T}^{\infty}} \Big\{ \int_T^{\infty} e^{-\rho t} \Big(\sum_{i=1}^{2} \Big(U(C_i(t)) - \Psi(K_i(T)) \Big) - 2D(P(t)) \Big) \mathrm{d}t \Big\}, \tag{6}$$

subject to (3), given the level of pollution stock at time T. The corresponding HJB equation is given by (note that we have an infinite horizon and no explicit dependence on

[9]The recent paper by Schumacher (2019) introduces arguments in favor of a social planner solely using mitigation as a policy instrument. He argues that standard representative agent models disregard the public feature of mitigation, and disaggregating such a representative agent model would completely reduce the need for adaptation. We consider two separate countries and partly introduce a public versus private good tradeoff. If we were to compare a social planner model that solely has access to mitigation with a non-cooperative outcome in which there is mitigation and adaptation, we would observe a larger gap in pollution levels than in a situation in which a social planner also has access to adaptation.

[10]Throughout this document, notation is the following. The superscript C (MP) denotes the cooperative (non-cooperative) outcome. The first subscript A (B) denotes the post-shift (pre-shift) regime. If applicable, the second subscript denotes the partial derivative of value function V with respect to state variable x in regime $r \in \{A, B\}$: $V_{r,x}(x) = \frac{\partial V_r(x)}{\partial x}$. We suppress time-dependency or state-dependency where no confusion can arise.

time t; hence the problem is stationary):

$$\rho V_A^C = \max_{C_1,C_2} \Big\{ \sum_{i=1}^{2} \Big(U(C_i) - \Psi(K_i) \Big) - 2D(P) + V_{A,P}^C \Big(C_1 + C_2 - \delta P \Big) \Big\}, \tag{7}$$

which yields the decision rules:

$$C_i = \frac{a_i + V_{A,P}^C}{b_i}, i = 1, 2, \tag{8}$$

provided that $a_i + V_{A,P}^C \geq 0$. We only consider interior solutions throughout this paper and choose parameters such that this is satisfied.[11] One can verify that if we impose symmetry (7) is solved by

$$\hat{V}_A^C(P, K_1, K_2) = A_1 P^2 + A_2 P + A_3 + A_4 \Psi(K_1) + A_5 \Psi(K_2), \tag{9}$$

where

$$A_1 = \frac{b\rho + 2\delta b - \sqrt{(b\rho + 2b\delta)^2 + 32bd}}{8}, A_2 = \frac{4aA_1}{b(\rho + \delta) - 4A_1}, A_3 = \frac{(a + A_2)^2}{\rho b}, A_4 = A_5 = \frac{-1}{\rho}.$$

This is the social planner outcome as in Dockner and Long (1993) but with additional loss of welfare due to the regime shift. Post-regime shift, pollution stock evolves according to:

$$P(t) = \Big(P(T) - \frac{2(a + A_2)}{\delta b - 4A_1} \Big) e^{\frac{4A_1 - \delta b}{b}(t-T)} + \frac{2(a + A_2)}{\delta b - 4A_1}. \tag{10}$$

Before the regime shift, the social planner maximizes the welfare of both regions subject to the pollution dynamics and capital dynamics and given initial levels of pollution stock and capital stock:

$$\begin{aligned} V_B^C = V_{1B} + V_{2B} = \max_{\{C_1,C_2,I_1,I_2\}_{t=0}^{\infty}} \Big\{ E_0 \Big[\int_0^T e^{-\rho t} \Big(\sum_{i=1}^{2} \Big(U(C_i) - F(I_i) \Big) - 2D(P) \Big) \mathrm{d}t \\ + e^{-\rho T} V_A^C(P(T), K_1(T), K_2(T)) \Big] \Big\}. \end{aligned} \tag{11}$$

The social planner maximizes (11), subject to (3), non-negativity of investments, (4) and given (9). The corresponding HJB equation is given by:

$$\begin{aligned} \rho V_B^C = \max_{C_1,C_2,I_1,I_2} \Big\{ \sum_{i=1}^{2} \Big(U(C_i) - F(I_i) \Big) - 2D(P) - H(P)[V_B^C - V_A^C] \\ + V_{B,P}^C \Big(C_1 + C_2 - \delta P \Big) + \sum_{i=1}^{2} V_{B,K_i}^C \Big(I_i - \delta_K K_i \Big) \Big\}, \end{aligned} \tag{12}$$

[11] We are aware that this introduces conceptual challenges in the Markovian Nash Equilibrium. In the next section we address these concerns in more detail.

where the term $H(P)[V_B^C - V_A^C]$ denotes the expected welfare loss due to the regime shift (van der Ploeg & de Zeeuw, 2016). The maximization problem yields:

$$C_i = \frac{a_i + V^C_{B,P}}{b_i}, I_i = \max\left(0, \frac{V^C_{B,K_i} - \phi_i}{\chi_i}\right), i = 1, 2.$$

In Appendix A.3, we show how to solve this HJB equation by collocating on the value function on a set of sparse grid nodes.

4 Non-cooperative outcome

Next, we turn to the non-cooperative outcome. We choose to derive the Markov Perfect Nash Equilibrium (MPNE), an equilibrium concept where each country has state-dependent strategies. The MPNE is preferred over the commonly derived Open-Loop Nash Equilibrium (OLNE) where decisions are only functions of time. The MPNE allows countries to condition their decisions on the current state of the system and is therefore subgame-perfect. Since there is no explicit time dependence in the objective function and the time horizon is infinite, the problem is stationary. Thus, we can drop the time dependency and restrict ourselves to time-stationary candidate strategies (Dockner & Long, 1993; Dockner, Jorgensen, Long, & Sorger, 2000; Kossioris et al., 2008). After the regime shift has occured at time T, we study a standard non-cooperative pollution game, with the additional feature of constant damages $\Psi_i(K_i(T)) = \frac{A_i Z_i}{Z_i + K_i(T)}$. This does not significantly alter the analysis compared to Dockner and Long (1993), but for completeness we repeat it here. The transition between the pre- and post-shift regimes is stochastic, but the regimes are deterministic. Therefore, we can apply Theorem 8.2 of Dockner et al. (2000) to derive a Markov Perfect Nash Equilibrium for piecewise-deterministic differential games. The Markovian Strategy ξ_i of country $i = 1, 2,\ i \neq j$, is given by:

$$\xi_i(P, K_i, K_j) = \begin{cases} \xi_i^B(P, K_i, K_j) & \text{if } t < T, \\ \xi_i^A(P, K_i, K_j) & \text{if } t \geq T. \end{cases} \tag{13}$$

The post-shift Markovian Strategies have to satisfy the following set of HJB equations on the whole state space such that the relevant value function is differentiable:

$$\rho V^{MP}_{iA} = \max_{C_i} \left\{ U(C_i) - \Psi(K_i) - D(P) + V^{MP}_{iA,P}\Big(C_i + \xi_j^A - \delta P\Big) \right\}, \tag{14}$$

$$\rho V^{MP}_{jA} = \max_{C_j} \left\{ U(C_j) - \Psi(K_j) - D(P) + V^{MP}_{jA,P}\Big(\xi_i^A + C_j - \delta P\Big) \right\}. \tag{15}$$

In this paper, we focus on linear Markov Strategies as long as they exist (these then also satisfy the often imposed requirement of Lipschitz continuity).[12] Due to the piecewise-

[12] There has been an extensive discussion on the appropriate choice of the strategy set of Markovian strategies for a differential game, see Jaakkola and Wagener (2023) and references therein. In Jaakkola and Wagener (2023) the authors show that the 'classical' equilibrium that results from agents playing linear Markovian strategies is Pareto dominated by all other symmetric equilibria and introduce an approach to identify the whole set of admissible Markovian strategies and allow for discontinuities in the strategies.

deterministic structure and the appearance of multiple state variables, we cannot apply the recent theorems developed in Jaakkola and Wagener (2023), who consider an univariate, deterministic setting. We take a tractable approach by restricting to linear strategies in the post-shift world. This allows to obtain a closed-form solution for the post-shift value function. In this type of piece-wise deterministic pollution game, a time-variant hazard rate will yield non-linear strategies before the regime shift has occured.

In the following analysis, we focus on (where applicable) linear strategies that result in interior solutions and assume, in both the benchmark and Mitigation-Adaptation model, that the value function is differentiable on the whole state space. In practice, our restrictions on the differential game imply that post-shift consumption strategies are linear in the pollution stock, and pre-shift we obtain non-linear strategies as the hazard rate is not constant. If we were to consider non-linear strategies post-shift, the major difference in the discussion compared to linear strategies is that the gap between post- and pre-shift steady state levels of pollution is smaller, which is a direct consequence of the fact that non-linear strategies are more efficient in pollution control, but extensive analysis of these scenarios will be left for further research.

Post-shift, the only relevant state variable is pollution stock, as the capital stock is only a state variable up to time T, and afterwards it is taken as given. Similar to the social planner scenario, this problem can be solved by means of the method of undetermined coefficients. Under the assumptions of symmetry and linear strategies, one can show that the value function after the regime shift has to satisfy

$$\hat{V}_{iA}^{MP}(P) = B_1 P^2 + B_2 P + B_3 + B_4 \Psi(K_i(T)), i = 1, 2,$$

where

$$B_1 = \frac{b\rho + 2\delta b - \sqrt{(b\rho + 2b\delta)^2 + 24bd}}{12}, B_2 = \frac{4aB_1}{b(\rho+\delta) - 6B_1}, B_3 = \frac{a^2 + 4aB_2 + 3B_2^2}{2\rho b}, B_4 = \frac{-1}{\rho}.$$

The transition path for pollution post-shift is given by:

$$P(t) = \Big(P(T) - \frac{2(a+B_2)}{\delta b - 4B_1}\Big) e^{\frac{4B_1 - \delta b}{b}(t-T)} + \frac{2(a+B_2)}{\delta b - 4B_1}, \tag{16}$$

which implies convergence post-shift towards a pollution level $\bar{P}^{A,MP}$.
Let $V_{iB}^{MP} = V_{iB}^{MP}(P, K_i, K_j), V_{jB}^{MP} = V_{jB}^{MP}(P, K_i, K_j)$ denote the value functions pre-shift, which have to satisfy the following set of HJB equations:

$$\begin{aligned}
\rho V_{iB}^{MP} &= \max_{C_i, I_i} \Big\{ U(C_i) - F(I_i) - D(P) - H(P)[V_{iB}^{MP} - V_{iA}^{MP}] + V_{iB,P}^{MP}\Big(C_i + \xi_{j,C}^B - \delta P\Big) \\
&\quad + V_{iB,K_i}^{MP}\Big(I_i - \delta_K K_i\Big) + V_{iB,K_j}^{MP}\Big(\xi_{j,I}^B - \delta_K K_j\Big)\Big\}, \qquad (17) \\
\rho V_{jB}^{MP} &= \max_{C_j, I_j} \Big\{ U(C_j) - F(I_j) - D(P) - H(P)[V_{iB}^{MP} - V_{jA}^{MP}] + V_{jB,P}^{MP}\Big(\xi_{i,C}^B + C_j - \delta P\Big) \\
&\quad + V_{jB,K_i}^{MP}\Big(\xi_{i,I}^B - \delta_K K_i\Big) + V_{iB,K_j}^{MP}\Big(I_j - \delta_K K_j\Big)\Big\}. \qquad (18)
\end{aligned}$$

In Appendix A.3, we show how to solve this set of HJB equations by collocating on the value functions on a set of sparse grid nodes.

5 Discussion of Results

As a default, we consider the following default parameterization: $a = 1.6, b = 1, \rho = 0.025, d = 0.25, \delta = 0.05, \delta_K = 0.05, \phi = 1, \chi = 1, Z = 1, \lambda = 0.008, \gamma = 0.008, A = 1$. These parameters are chosen such that we closely match previous work in pollution games (Nkuiya, 2015) and in the default parameterization there is a positive level of adaptive capital built up. In our analysis, we will vary the parameters A (size of the shock) and λ (sensitivity of the hazard rate with respect to the pollution stock) to see how robust our findings are. In the Appendix A.4 we show that our results are robust to variations in the discount rate ρ.

Before studying the interaction between mitigation and adaptation, it is important to note that, in both the cooperative and non-cooperative outcome, the level of adaptive capital does not directly affect the post-shock consumption decision as we only consider proactive investments and the impact of the shock materializes immediately. All the mitigation-adaptation interaction appears in the pre-shock world. Our focus in the remainder of this section is thus on the interaction between adaptation and mitigation in anticipation of the regime shift: the effect of a possibility of adaptation on efforts to lower the risk of disaster. This discussion contains three sections. First, we illustrate how precautionary behaviour takes place and why the timing of the regime shift matters. Second, we study the effect adaptation has on mitigation under non-cooperation. Third, we compare the cooperative and non-cooperative outcome and show how our results relate to previous literature.

5.1 Illustrating dynamics under the risk of a regime shift and precautionary behaviour

It is instructive to briefly discuss how the dynamical system behaves under a possible regime shift. We illustrate this for a single decision maker to reduce the number of dimensions to two, but the dynamics are similar for the social planner outcome or the MPNE, *mutatis mutandis*. Consider Figure 1 and assume that before the regime shift has occured, the system starts out at time $t = 0$ with initial stocks $P(0), K(0)$. Before the regime shift, the system moves towards the unstable steady state $\bar{P}_B, \bar{K}$.

As the hazard rate is strictly larger than zero, at some finite, *stochastic* time T_2 the regime shift takes place, and at that moment the stocks are $P(T_2), K(T_2)$. At that point, dynamics switch from the thick line onto the dotted line. The capital stock solely depreciates from time T_2 onwards as we only consider proactive investments; in the long-run, the capital stock will equal zero. The marginal costs of increasing consumption are lower post-shift than pre-shift as there is no additional incentive to lower consumption as there is no possibility to reduce risk. Hence, the system switches dynamics and follows a trajectory traced out by the red line towards an equilibrium $\bar{P}_A, 0$. Necessarily, we should have $\bar{P}_A \geq \bar{P}_B$ as the benefits of mitigation are higher pre-shift than post-shift.

Regardless of when the regime shift takes places, the system post-shift moves towards the same level of pollution. Consider the dynamics that result from following the dashed line in Figure 1. The system tips starts out on the solid line, but tips earlier at $T_1 < T_2$. Capital stock is lower at $K(T_1) < K(T_2)$, and the system follows a trajectory over the blue line towards the equilibrium $\bar{P}_A, 0$.

With Figure 1 in mind, we note that the presence of a possible regime shift serves as an implicit mechanism to lower emissions, which means that if the regime shift takes place later in the future the system will be less polluted for a longer time. This is precautionary behaviour; even the risk of disaster is enough to change behaviour and aim for a lower level of pollution stock. In the next subsection, we discuss the dynamics of a regime shift in the MPNE and the strength of the precautionary behaviour by investigating the difference between pre- and post-shock steady state of pollution, how this differs in the benchmark and full model, and how this changes depending on the parameterization.

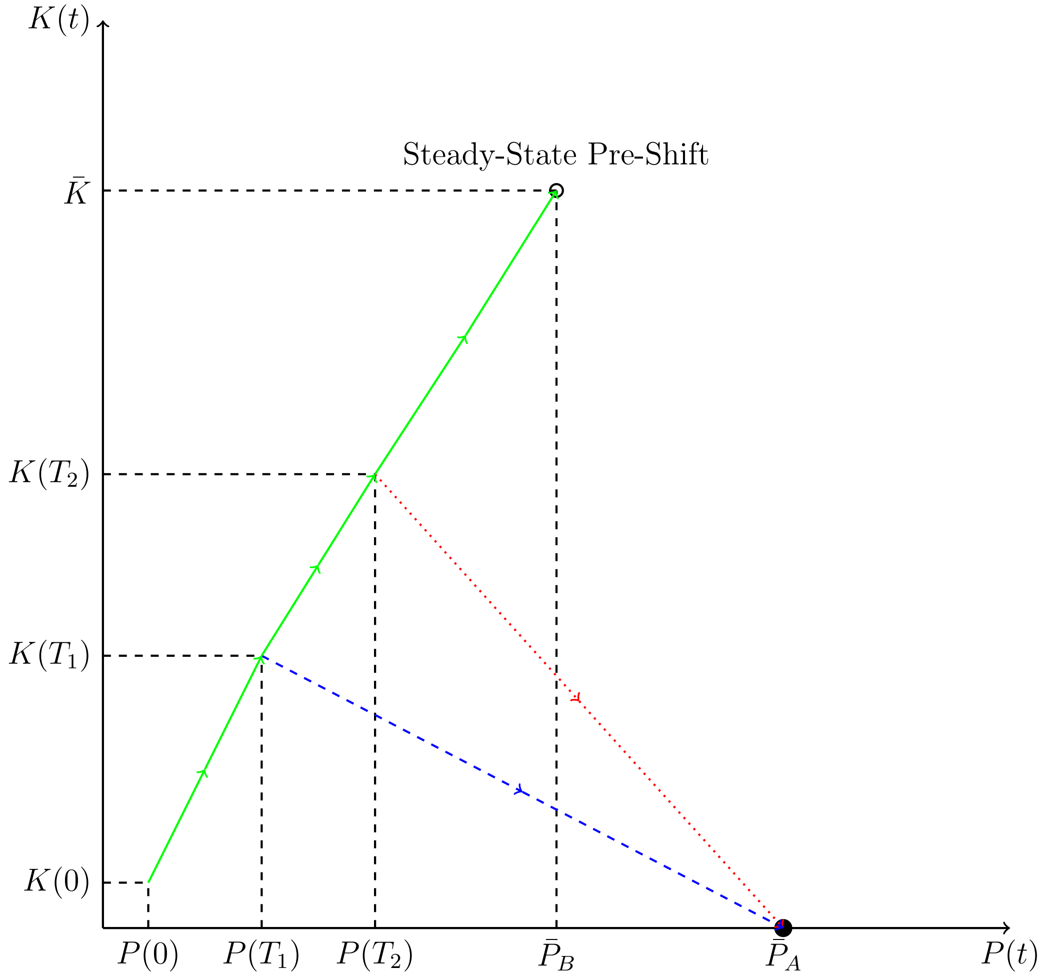

Figure 1: Dynamics under a regime shift and resulting precautionary behaviour. Notation is the following: $P(t), K(t)$ are pollution and capital stock, respectively, at time t in the system; T_1, T_2 are two realization of the stochastic time at which the regime shift can take place; $\bar{P}_B, \bar{K}$ are the steady states towards which the system moves before the regime shift has taken place; $\bar{P}_A$ is the steady state level of pollution towards which the system moves after the regime shift has taken place.

5.2 Effects of adaptation under non-cooperation

Next, we present two figures that study the effect of adaptation on steady state levels of pollution stock. It is important to note that in the both figures, the thick horizontal line corresponds to the steady state pollution level post-shift. The steady state depends on neither the size of the shock, A nor the sensitivity of the hazard rate, λ. The reason is straightforward: behaviour post-shift is not driven by the possibility of a regime shift, as the shock has already taken place, which can also be seen in equation (16).

First, Figure 2 displays the role of the size of the shock A. We vary the parameter A and calculate steady state levels of pollution in different regimes and scenarios for a non-cooperative outcome. The thick horizontal line gives the steady-state level of pollution post-shift. The dotted (dashed) line gives the steady state level of pollution pre-shift for a model with mitigation and adaptation (mitigation). We see that if the shock is zero, $A = 0$, in both the benchmark and the Mitigation and Adaptation (MA) model the target steady state levels of pollution are equal; there is no need to mitigate to reduce the risk of disaster as there is no disaster. For low levels of A, the difference in steady state level of pollution between the two models is negligible. However, as A becomes larger, the gap between the steady state level of pollution in the benchmark and in the MA-model increases. As the impact of the shock becomes larger, the possibility of adaptation reduces the incentives to mitigate, and this effect becomes larger as the shock increases: the gap between the benchmark and MA target steady state widens.

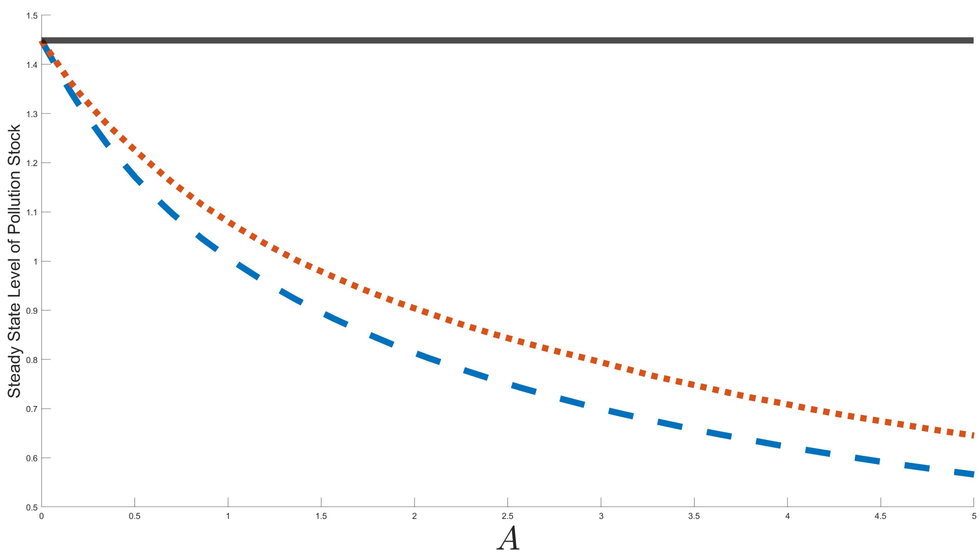

Figure 2: Steady state levels of pollution as a function of A for the benchmark and full model pre- and post-shift, MPNE. The thick horizontal line gives the steady-state level of pollution post-shift. The dotted line gives the steady state level of pollution pre-shift for a model with mitigation and adaptation. The dashed line gives the steady state level of pollution pre-shift for a model with mitigation.

In Figure 3, the role of λ is investigated. We vary the level of λ and calculate the steady state level of pollution. Again, the thick horizontal line gives the steady-state level of pollution post-shift. The dotted (dashed) line gives the steady state level of pollution pre-shift for a model with mitigation and adaptation (mitigation). At $\lambda = 0$, the hazard rate is independent of the level of pollution stock. This special case results in separation of the adaptation and mitigation decision; the existence of a regime shift does not alter mitigation incentives if the only possible response to a regime shift is to adapt. As a result, in both the benchmark and MA-model the system moves to the same steady state. However, when $\lambda > 0$, the benchmark model involves more mitigation than the MA-model, and this gap widens as the sensitivity λ of the hazard rate to the pollution stock increases.

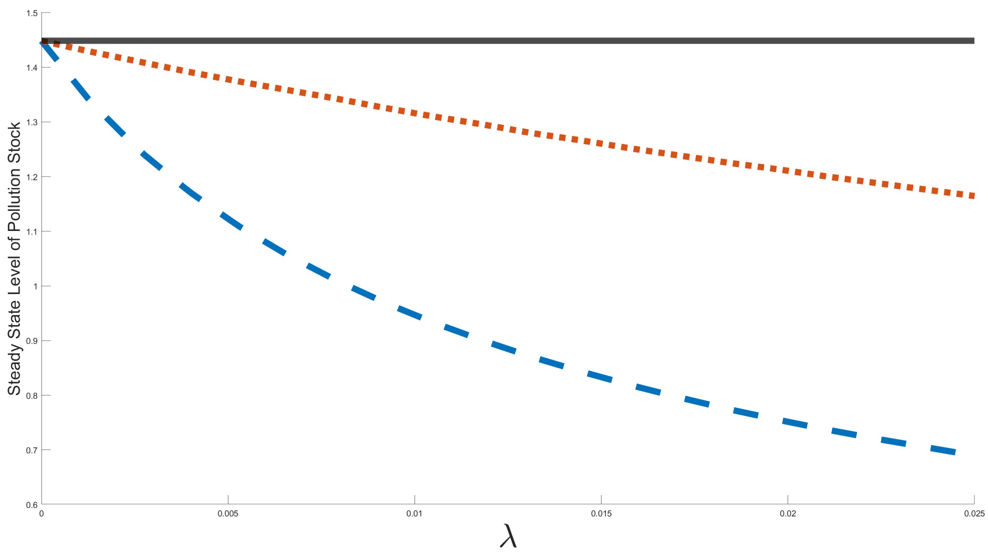

Figure 3: Steady state levels of pollution as a function of λ for the benchmark and full model pre- and post-shift, MPNE. The thick horizontal line gives the steady-state level of pollution post-shift. The dotted line gives the steady state level of pollution pre-shift for a model with mitigation and adaptation. The dashed line gives the steady state level of pollution pre-shift for a model with mitigation.

The previous figures showed a large gap between the steady states of the benchmark and MA-model. The economic intuition is the following. Consider the marginal benefits of mitigation in the benchmark and MA-model. In the benchmark model, the benefits of mitigation can be decomposed in two parts: a direct decrease in pollution damages $D(P)$ and a reduction in the hazard rate, which lowers the net effect (i.e. adjusted for uncertainty) the regime shift has on pre-shift welfare. In the MA-model, there is a similar decomposition of benefits. However, the second term is lower than in the benchmark scenario, as the net effect the regime shift has on welfare is lower as adaptive capital is built up. As a result, the returns to mitigation are lower when adaptation is *present and used*, and thus there will be less mitigation in the MA-model. Given this decomposition of marginal benefits of mitigation, the dependency of the gap between the steady states on the parameters A, λ can be explained. When A increases, the returns to mitigation increase. These returns are higher in the benchmark model than in the MA-model, as in the MA-model there will be a possibility to lower the impact. When λ increases, returns to mitigation in the benchmark model become increasingly larger as the probability can more heavily be reduced when mitigation increases. In the MA-model, the incentives to mitigate also increase in λ, but the returns are lower as adaptation takes away part of the net impact.

These findings can be strengthened by considering strategic motives. Based on the decomposition of the marginal damages, if region j increases its adaptation investments, region i expects that this will lead to an increase in emissions by region j and therefore decreases its emissions and increases its adaptation investments. In a symmetric setting, this mechanism also goes the other way around; region j observes that region i increases adaptation, and therefore also lowers emissions and increases its adaptation investments. This mechanism has also been discussed in Vardar and Zaccour (2018), but it is also present in our richer model. We will explain in the next subsection in more detail why we obtain a similar mechanism.

The two figures also indicate the strength of the precautionary effect. As discussed in figure 1, the possibility of a regime shift serves as an implicit driver to lower emissions. The strength of this effect can be seen by comparing the steady states pre- and post-regime shift. Consider figures 2 and 3. In both figures, the thick horizontal line depicts the steady state post-shift. Comparing the dashed (Mitigation) and dotted ((Mitigation-Adaptation)) curves, the difference between steady states pre- and post-regime shift decreases when adaptation becomes a possibility; there will be less of a reduction in emissions due to precautionary behaviour when part of the precaution can also be done by means of adaptation. But this in turn implies that in general, there will be more hazard in the MA-model than in the benchmark, such that, not only the probability of the regime shift taking place at a certain moment in time is larger in the former model, there is also less incentive to reduce emissions: both the time spent in the pre-shift phase as well as the associated benefits of staying in the pre-shift phase are lower. The possibility of adaptation both weakens the precautionary motive and also yields a substantial increase in the hazard.

5.3 Gains from cooperation in pollution control

It is also worthwhile to discuss the gains from being able to coordinate cooperation. The eminent gain is less pollution, as the social planner outcome rightfully acknowledges that there are negative spillovers from one country to the other. When adaptation is present, a social planner allows for more pollution (as pointed out by Zemel (2015)), but the level of pollution in the non-cooperative outcome also increases as adaptation is possible. As the effect under non-cooperation is larger, the gap between the two steady states increases: coordinating cooperation becomes more attractive when adaptation is possible than in the case in which adaptation is not possible.

Figures 4 and 5 displays the gains in pollution control. For different values of the size of the shock and the sensitivity of the hazard rate with respect to pollution stock,

A, λ, respectively, the figures display the steady state level of pollution. Specifically, the dotted (dashed) lines correspond to the steady state level of pollution for a social planner model with mitigation (mitigation and adaptation) and the dashed-dotted (thick) lines correspond to the non-cooperative outcome with mitigation (mitigation and adaptation) for different values of A (figure 4) and λ (figure 5). From the two figures we can infer that the option to adapt does not heavily affect mitigation in the social optimum as the spread between the lower two curves is negligible. However, the non-cooperative outcome suffers heavily from the option to adapt; the gains from cooperation in terms of efficient pollution control therefore increase heavily if adaptation is present.
Two comparisons with previous literature can be made. First, we showed that modelling cooperation and non-cooperation can affect the results obtained. Our cooperative scenario aligns with Zemel (2015); a social planner can allow for a combination of mitigation and adaptation. However, if we allow for multiple interacting decision makers that do not cooperate, there is a loss of contributions to the public good if adaptation is possible. Second, in a richer model where we take uncertainty, non-linear damages and an infinite time horizon into account, we obtain similar qualitative results as Vardar and Zaccour (2018); the option to adapt gives countries incentive to mitigate less. Vardar and Zaccour (2018) do not do not consider the aforementioned model features but postulate that both countries face a finite time horizon, no uncertainty and have a gradual damage function of the form $D(P, K_i) = \frac{P^2}{2} - K_i P$ (cf. equation three of Vardar and Zaccour (2018)), that depends on both the pollution stock and the level of adaptive capital. Our results do not differ as the decision makers in our model maximize expected utility, and the hazard rate formulation and the utility functions specification make it such that agents only care about a specific *interaction effect* between pollution and adaptive capital stock $H(P)V_i^A(P, K_i)$ (which appears in equations (12), (17)-(18)). This interaction term shares similar multiplicative structure as the damage function specified by Vardar and Zaccour (2018).

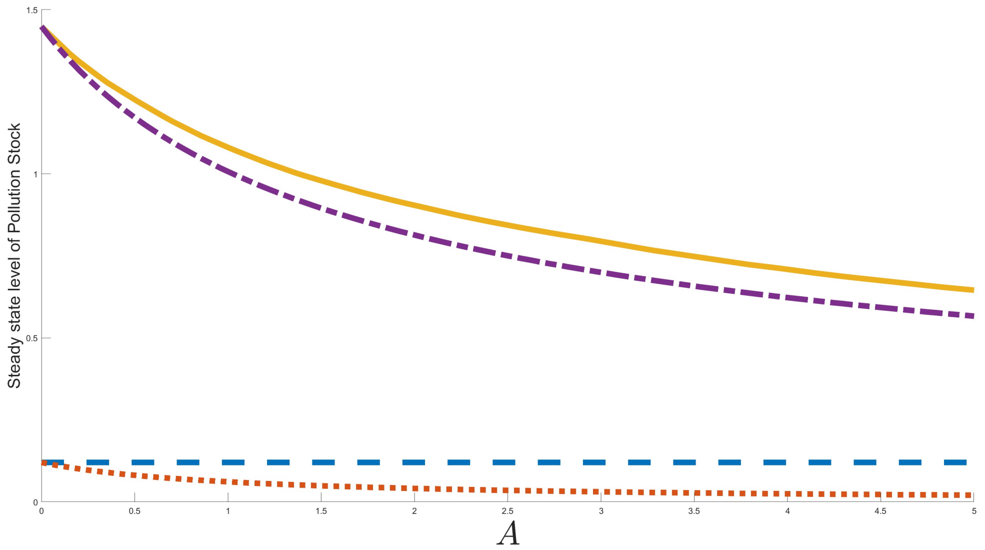

Figure 4: Gains from coordinating cooperation in pollution control for different levels of the size of the shock A in four different model specifications. The dotted (dashed) lines correspond to the steady state level of pollution for a social planner model with mitigation (mitigation and adaptation) and the dashed-dotted (thick) lines correspond to the non-cooperative outcome with mitigation (mitigation and adaptation).

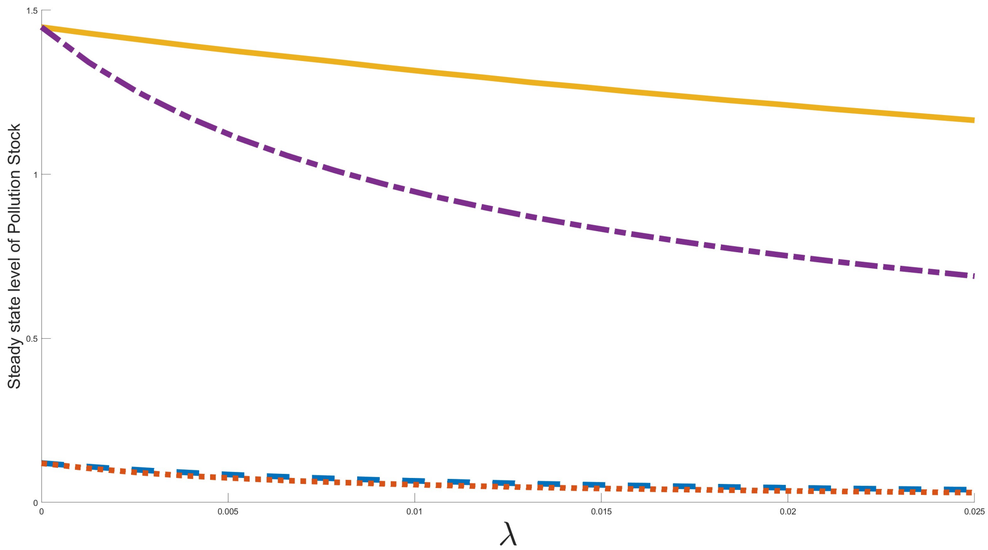

Figure 5: Gains from coordinating cooperation in pollution control for different levels of the size of the shock λ in four different model specifications. The dotted (dashed) lines correspond to the steady state level of pollution for a social planner model with mitigation (mitigation and adaptation) and the dashed-dotted (thick) lines correspond to the non-cooperative outcome with mitigation (mitigation and adaptation).

6 Conclusion

In this paper, we studied the tradeoff between mitigation and adaptation in the presence of an uncertain environmental regime shift. Previous literature has either neglected uncertainty and regime shifts or did not consider the fact that adaptation is a local policy instrument and mitigation a global one. We incorporated these model elements in a pollution game with an irreversible regime shift and studied how adaptation affects incentives to mitigate and precautionary behaviour. We studied a social planner outcome and a non-cooperative outcome in which each country uses Markov Perfect strategies. We obtained closed form solutions for the post-shift value functions and used collocation on sparse grids to obtain approximate solutions for the value functions pre-shift.

Our findings are the following. First, mitigation incentives are reduced more heavily in a non-cooperative than in a cooperative outcome. Second, free-riding increases heavily when both the size of the shock or the sensitivity of the hazard rate with respect to pollution increase. Finally, the option of adaptation increases risk of disaster heavily under non-cooperation, making the case to either not cooperate but focus on mitigation or to cooperate more attractive.

Our model shows the importance of considering non-cooperative outcomes where there is tension between public and private goods. We show that, contrary to single decision maker frameworks (Zemel, 2015), the availability of private goods crowds out contributions to the public good. Allowing for uncertainty, non-linear damages and an infinite time horizon, we find that the results of Vardar and Zaccour (2018) are robust to our richer model.

Given our results, policy makers should keep two things in mind. First, if cooperation would be possible, it would be good to consider the public nature of mitigation, and that, although adaptation can cover part of the damages, its implementation would result in more risk of crossing tipping points. Second, if countries cannot coordinate cooperation in pollution control, they can take into account that the option to adapt gives more incentive to free-ride.

Further research could go in several directions. First, asymmetries in the form of vulnerability and/or capability to respond to disaster can be studied. This can provide insights into how gains of cooperation should be shared among heterogeneous countries. Second, we could allow for a more detailed description of the economy, as in for instance van der Ploeg and de Zeeuw (2016). This allows us to study carbon taxation in more detail. Finally, alternative specifications of the impact of the regime shift could be considered. For instance, one could consider that the damage stream of pollution increases, which has as a consequence that the impact of the regime shift is spread out over time instead of materialized immediately. Or, we could allow for recurring shocks. We leave these considerations to further research.

A Appendix

A.1 Post-shift value functions and dynamics

This section of the appendix shows how we derive the post-shift value functions for the social planner and MPNE.

Social Planner

The HJB is given by:

$$\rho V_A^C = \max_{C_1,C_2} \Big\{ \sum_{i=1}^{2} \Big(U(C_i) - \Psi(K_i) \Big) - 2D(P) + V_{A,P}^C \Big(C_1 + C_2 - \delta P \Big) \Big\},$$

and thus the controls have to satisfy $C_i = \frac{a_i + V_{A,P}^C}{b_i}$. Substitute the controls into the HJB equation, impose symmetry and guess the following form for the value function:

$$\hat{V}_A^C = A_1 P^2 + A_2 P + A_3 + A_4 \Psi(K_1) + A_5 \Psi(K_2).$$

Substitute $\hat{V}_A^C, \hat{V}_{A,P}^C$ into the maximized HJB-equation and collect terms:

$$\begin{aligned} A_1 &= \frac{b\rho + 2\delta b - \sqrt{b^2(\rho + 2\delta)^2 + 32bd}}{8}, \\ A_2 &= \frac{4aA_1}{b(\rho + \delta) - 4A_1}, \\ A_3 &= \frac{(a + A_2)^2}{\rho b}, \\ A_4 &= A_5 = \frac{-1}{\rho}. \end{aligned}$$

The steady state $\bar{P}^{A,SP}$ can be found if we substitute the decision rules for consumption into the dynamics for P and is unique. Stability requires that $\frac{4A_1 - \delta b}{b} < 0$, which is satisfied for any non-negative parameter pair b, δ, ρ.

Markovian Competition

Linear Markov strategies imply that an adequate guess for the value function is a 2nd-order polynomial in P, and a part in K:

$$\hat{V}_{iA}^{MP} = B_1 P^2 + B_2 P + B_3 + B_4 \Psi(K_i).$$

Impose symmetry and substitute the strategies and values function into the HJB equation to obtain the maximized HJB. Collect terms to find:

$$\begin{aligned}
B_1 &= \frac{b\rho + 2\delta b - \sqrt{b^2(\rho+2\delta)^2 + 24bd}}{12},\\
B_2 &= \frac{4aB_1}{b(\rho+\delta) - 6B_1},\\
B_3 &= \frac{a^2 + 4aB_2 + 3B_2^2}{2\rho b},\\
B_4 &= \frac{-1}{\rho}.
\end{aligned}$$

The steady state $\bar{P}^{A,MP}$ can be found if we substitute the decision rules for consumption into the dynamics for P and is unique. Stability requires that $\frac{4B_1 - \delta b}{b} < 0$, which is satisfied for any non-negative parameter pair b, δ, ρ.

A.2 Derivation of the Benchmark Model

To make a distinction between the model with mitigation and the model with mitigation and adaptation, let the value functions in the former case be denoted as $W_B^C(P), W_B^{MP}(P)$, and analogously for the value functions in the pre-shift regime. It is straightforward to write down the HJB equations for each regime. For the social planner the post- and pre-shift HJB equations are given by:

$$\begin{aligned}
\rho W_A^C &= \max_{C_1,C_2}\Big\{\sum_{i=1}^{2} U(C_i) - 2A - 2D(P) + W_{A,P}^C\Big(C_1 + C_2 - \delta P\Big)\Big\},\\
\rho W_B^C &= \max_{C_1,C_2}\Big\{\sum_{i=1}^{2} U(C_i) - 2D(P) - H(P)[W_B^C - W_A^C] + W_{B,P}^C\Big(C_1 + C_2 - \delta P\Big)\Big\}.
\end{aligned}$$

For the MPNE, one can write down two systems of HJB equations, one for each regime. Let $\omega_i(P)$ be the stationary Markovian strategies for each country. Post-shift, the relevant HJB equations are:

$$\begin{aligned}
\rho W_{iA}^{MP} &= \max_{C_i}\Big\{U(C_i) - D(P) + W_{iA,P}^{MP}\Big(C_i + \omega_j^A - \delta P\Big)\Big\},\\
\rho V_{jA}^{MP} &= \max_{C_j}\Big\{U(C_j) - D(P) + W_{jA,P}^{MP}\Big(\omega_i^A + C_j - \delta P\Big)\Big\}.
\end{aligned}$$

Pre-shift, the relevant HJB equations are:

$$\begin{aligned}
\rho W_{iB}^{MP} &= \max_{C_i}\Big\{U(C_i) - D(P) - H(P)[W_{iB}^{MP} - W_{iA}^{MP}] + W_{iB,P}^{MP}\Big(C_i + \omega_j^B - \delta P\Big)\Big\},\\
\rho W_{jB}^{MP} &= \max_{C_j}\Big\{U(C_j) - D(P) - H(P)[W_{jB}^{MP} - W_{jA}^{MP}] + W_{jB,P}^{MP}\Big(\omega_i^B + C_j - \delta P\Big)\Big\}.
\end{aligned}$$

In the MPNE outcome, we can invoke symmetry and then reduce the system of HJB equations.

We solve the HJB equations for the MPNE and social planner for the 'mitigation model' by means of collocation using regular tensor products, as this problem only features one state variable, pollution stock. We provide an overview of the numerical procedure.

1. Gridpoints, basis functions and basis matrices.

   (a) For state variable P defined on the closed interval $[P^L, P^H]$, create the set $N_P = \{P_i\}_{i=1}^{n_P}$ of n_P Chebyshev nodes:

   $$P_i = \frac{P^L + P^H}{2} + \frac{P^H - P^L}{2} \cos\left(\frac{n_P - i + 0.5}{n_P}\pi\right),\ i = 1, \ldots, n_P.$$

   (b) The basis functions $b_{i_1}(P)$ are formed based on a full tensor product of Chebyshev polynomials $T(\cdot)$ of the first kind:

   $$b_{i_1}(P) = T_{i_1-1}(z^P),$$
   $$T_n(z) = \cos(\arccos(z) \cdot n),$$

   where z^P is the transformed grid such that the domain of P is normalized to the interval $[-1, 1]$.

   (c) The basis matrices corresponding to the value function and the partial derivative of the value function are given by:

   $$B(i,j) = b_j(P_i),\ B^P(i,j) = \frac{\partial b_j(P_i)}{\partial P}, i, j = 1, \ldots, n_P.$$

2. Operator equation. The value functions are approximated by means of the product of the basis matrix and the collocation vector: $W_B^{SP} = Bc^{SP}, W_B^{MP} = Bc^{MP}$ The following equations have to hold on all of the n Chebyshev nodes, creating a set of n equations with n unknowns (the collocation coefficients).

   (a) For the SP:

   $$0 = N(W_B^{SP}; c^{SP}) = -(\rho + H(P))W_B^{SP} + 2U(C^{*,SP}) - 2D(P) + H(P)W_A^{SP} + W_{B,P}^{SP}(2C^{*,SP} - \delta P),$$

   (b) For the MPNE:

   $$0 = N(W_B^{MP}; c^{MP}) = -(\rho + H(P))W_B^{MP} + U(C^{*,MP}) - D(P) + H(P)W_A^{MP} + W_{B,P}^{MP}(2C^{*,MP} - \delta P),$$

   where $C^{*,SP}, C^{*,MP}$ are the (symmetric) optimal consumption rules that follows from maximizing the RHS of the HJB equation in the SP and MPNE scenario. respectively.

3. Solve for the collocation coefficients. In both the SP and MPNE, the initial guess is $c_{init} = B^{-1}\bar{W}$, where W is the value function corresponding to the no-hazard case for both problems, respectively. Then, we solve the system of equations for the unknown collocation vector c with the 'fsolve' function in Matlab, first letting $\lambda = 0$ and gradually updating the guess towards the desired value of λ by using a continuation-like method.

A.3 Numerical Procedure: Collocation using sparse grids

In this section of the appendix, we describe the numerical procedure in more detail. In order to solve the non-linear PDEs, i.e. the HJB equations, we rely on the collocation method, a specific projection method that relies on polynomial approximation of an unknown function and its derivatives. The theory behind collocation is well-documented, see for instance Judd (1998); here we describe the implementation. We use the collocation method to solve all HJB equations pre-shift, in both the cooperative and non-cooperative scenarios. We use sparse grids to solve the HJB equations when both adaptation and mitigation are possible.

Solving a (set of) high-dimensional non-linear PDEs (the Hamilton-Jacobi-Bellman equations in the pre-shift scenario) is computationally intensive when using collocation with full tensor-products. In order to combat this, we implement sparse grids, for which theory was introduced by Smolyak (1963). Smolyak grids were first used in solving a high-dimensional dynamic economic model by Krueger and Kubler (2004). We show how to apply this method in order to solve the HJB for the social planner pre-shift and the set of HJB equations for the MPNE pre-shift.

The numerical procedure roughly follows the same steps as outlined in appendix A.2, except for step one. For state variable $x = \{P, K_1, K_2\}$, the set N_x consisting of n_x Chebyshev nodes defined on $[x^L, x^H]$ are given by:

$$x_i = \frac{x^L + x^H}{2} + \frac{x^H - x^L}{2} \cos\left(\frac{n_x - i + 0.5}{n_x}\pi\right), \; i = 1, \ldots, n_x.$$

Next, we create non-nested subsets of the full set of nodes (Judd et al., 2014). Formally:

$$N_{x1} = \{x_{\frac{n_x+1}{2}}\}, N_{x2} = \{x_1, x_{n_x}\}, N_{x3} = \{x_{\frac{1}{2}+\frac{n_x+1}{4}}, x_{\frac{n_x}{2}+\frac{n_x+1}{4}}\}, N_{x4} = N_x \setminus \bigcup_{i=1:3} N_{xi}.$$

The intersections of all subsets are empty and the union of all subsets is equal to the full set of Chebyshev nodes. The set of sparse gridpoints can then be constructed as:

$$N = \bigcup_{(i_1,i_2,i_3)\in\mathbb{Z}^3_{++},\, i_1+i_2+i_3\leq 3+\nu} N_{Pi_1} \times N_{K_1 i_2} \times N_{K_2 i_3}.$$

The constraints on the indices of the non-nested subsets provide the sparse tradeoff. Denote the cardinality of the grid by $\tilde{n}$ and the nodes in the sparse grid by $\{z_s\}_{s=1}^{\tilde{n}}$. We create for every state variable x non-nested subsets of basis functions evaluated in an arbitrary value x of the state variable mapped into the interval $[-1, 1]$:

$$S_x(\hat{x}) = \{b_x^j(\hat{x})\}_{j=1}^{n_x} = \{T_{j-1}(\hat{x})\}_{j=1}^{n_x},\ \hat{x} = 2\frac{x - x^L}{x^H - x^L} - 1,$$

where T_{j-1} are the Chebyshev polynomials of the first kind. The non-nested subsets of the set of basis functions and derivatives of basis functions are such that the cardinality of each subset i matches exactly to the cardinality of each associated subset of nodes N_{xi}:

$$S_{1x}(\hat{x}) = \{b_x^1(\hat{x})\}, S_{2x}(\hat{x}) = \{b_x^2(\hat{x}), b_x^3(\hat{x})\}, S_{3x}(\hat{x}) = \{b_x^4(\hat{x}), b_x^5(\hat{x})\}, S_{4x}(\hat{x}) = \{b_x^j(\hat{x})\}_{j=6}^{9},$$
$$S_{1x}^x(\hat{x}) = \left\{\frac{\partial b_x^1(\hat{x})}{\partial x}\right\}, S_{2x}^x(\hat{x}) = \left\{\frac{\partial b_x^2(\hat{x})}{\partial x}, \frac{\partial b_x^3(\hat{x})}{\partial x}\right\}, S_{3x}^x(\hat{x}) = \left\{\frac{\partial b_x^4(\hat{x})}{\partial x}, \frac{\partial b_x^5(\hat{x})}{\partial x}\right\}, S_{4x}^x(\hat{x}) = \left\{\frac{\partial b_x^j(\hat{x})}{\partial x}\right\}_{j=6}^{9}.$$

The sparse set of the product of basis functions evaluated in an arbitrary point can be constructed as:

$$S(P, K_1, K_2) = \bigcup_{(i_1,i_2,i_3)\in\mathbb{Z}_{++}^3,\ i_1+i_2+i_3\leq 3+\nu} S_{i_1P}(P) \times S_{i_2K_1}(K_1) \times S_{i_3K_2}(K_2).$$

Similarly, we can also create the sparse set of basis functions where one basis function is differentiated:

$$S^P(P, K_1, K_2) = \bigcup_{(i_1,i_2,i_3)\in\mathbb{Z}_{++}^3,\ i_1+i_2+i_3\leq 3+\nu} S_{i_1P}^P(P) \times S_{i_2K_1}(K_1) \times S_{i_3K_2}(K_2),$$
$$S^{K_1}(P, K_1, K_2) = \bigcup_{(i_1,i_2,i_3)\in\mathbb{Z}_{++}^3,\ i_1+i_2+i_3\leq 3+\nu} S_{i_1P}(P) \times S_{i_2K_1}^{K_1}(K_1) \times S_{i_3K_2}(K_2),$$
$$S^{K_2}(P, K_1, K_2) = \bigcup_{(i_1,i_2,i_3)\in\mathbb{Z}_{++}^3,\ i_1+i_2+i_3\leq 3+\nu} S_{i_1P}(P) \times S_{i_2K_1}(K_1) \times S_{i_3K_2}^{K_2}(K_2).$$

Finally, we create basis matrices that correspond to the value function and the partial derivatives of the value function, respectively, with elements $(i, j),\ i, j = 1, 2, \ldots, \tilde{n}$:

$$B(i, j) = S_j(z_i),$$
$$B^P(i, j) = S_j^P(z_i),$$
$$B^{K_1}(i, j) = S_j^{K_1}(z_i),$$
$$B^{K_2}(i, j) = S_j^{K_2}(z_i),$$

where $S_j(z_i)$ denotes the j-th element of the set S evaluated in the i-th sparse-gridpoint z_i. We then collocate on the value functions in the system of HJB equation, and create operator equations that solely are functions of the unknown coefficient vector. The solution procedure is then similar to step three in appendix A2.1. For completeness, we provide the operator equations for the SP and MPNE. Note that we can approximate the value function $V_B^{SP} = Bc$, and in turn also can approximate the derivatives of the value function by multiplying the relevant basis matrix with the collocation vector. The operator equation for the SP is:

$$
\begin{aligned}
N^{SP}(V_B^{SP};c) = &-(\rho + H(P))V_B^{SP} + U(C_1^*) + U(C_2^*) - F(I_1^*) - F(I_2^*) - 2D(P) + H(P)V_A^{SP} \\
&+ V_{B,P}^{SP}\Big(C_1^* + C_2^* - \delta P\Big) + V_{B,K_1}^{SP}\Big(I_1^* - \delta_K K_1\Big) + V_{B,K_2}^{SP}\Big(I_2^* - \delta_K K_2\Big),
\end{aligned}
$$

where we denote $C_1^*, I_1^*, C_2^*, I_2^*$ as the control rules that maximize the RHS of the HJB equation. The two operator equations define a system of $\tilde{n}$ equations with $\tilde{n}$ unknowns; the vector c. We let $n_i = 9$, $\forall i$ and use a precision of $\nu = 3$, which results in a system of 69 equations, opposed to 729 equations when a non-sparse grid is implemented. Not only is the sparse grid methods faster (the system of equations to solve is considerably smaller), convergence properties of the root-finding algorithm are also much better. We employ a continuation-like method to solve for the coefficient vector. We first solve a problem with a constant hazard rate, where the initial guess is equal to the coefficient vector corresponding to the post-shift value function. We then use the resulting coefficient vector to solve the problem with a time-variant hazard rate. The normalized residual over the set of evenly spaced sparse nodes is at least of order 10^{-4}.

Note that we can approximate the value function $V_{iB}^{MP} = Bc_1, V_{jB}^{MP} = Bc_2$, and in turn also can approximate the derivatives of the value function by multiplying the relevant basis matrix with the collocation vector. The operator equations for the MPNE are:

$$
\begin{aligned}
N_1(V_{iB}^{MP}, V_{jB}^{MP}; c_1, c_2) = &-(\rho + H(P))V_{iB}^{MP} + U(C_i^*) - F(I_i^*) - D(P) + H(P)V_{iA}^{MP} \\
&+ V_{iB,P}^{MP}\Big(C_i^* + C_j^* - \delta P\Big) + V_{iB,K_i}^{MP}\Big(I_i^* - \delta_K K_i\Big) + V_{iB,K_j}^{MP}\Big(I_j^* - \delta_K K_j\Big), \\
N_2(V_{iB}^{MP}, V_{jB}^{MP}; c_1, c_2) = &-(\rho + H(P))V_{jB}^{MP} + U(C_j^*) - F(I_j^*) - D(P) + H(P)V_{jA}^{MP} \\
&+ V_{jB,P}^{MP}\Big(C_i^* + C_j^* - \delta P\Big) + V_{jB,K_i}^{MP}\Big(I_i^* - \delta_K K_i\Big) + V_{jB,K_j}^{MP}\Big(I_j^* - \delta_K K_j\Big),
\end{aligned}
$$

where we denote $C_i^*, I_i^*, C_j^*, I_j^*$ as the control rules that maximize the RHS of the HJB equations. The two operator equations define a system of $2\tilde{n}$ equations with $2\tilde{n}$ unknowns; the vectors c_1, c_2. We let $n_i = 9$, $\forall i$ and use a precision of $\nu = 3$, which results in a system of 138 equations, opposed to 1458 equations when non-sparse grids are implemented.

A.4 Robustness check

In this section, we consider the sensitivity of our results with respect to the discount rate ρ. In figures 6 and 7 , we study the role of the discount rate ρ for the model with a quadratic hazard rate: we vary $\rho \in [0.01, 0.05]$. We see the same qualitative results as in the baseline parameterization: the option to adapt gives countries more incentive to free-ride and the gains from coordinating cooperation increase. These effects are amplified as the discount rate increases.

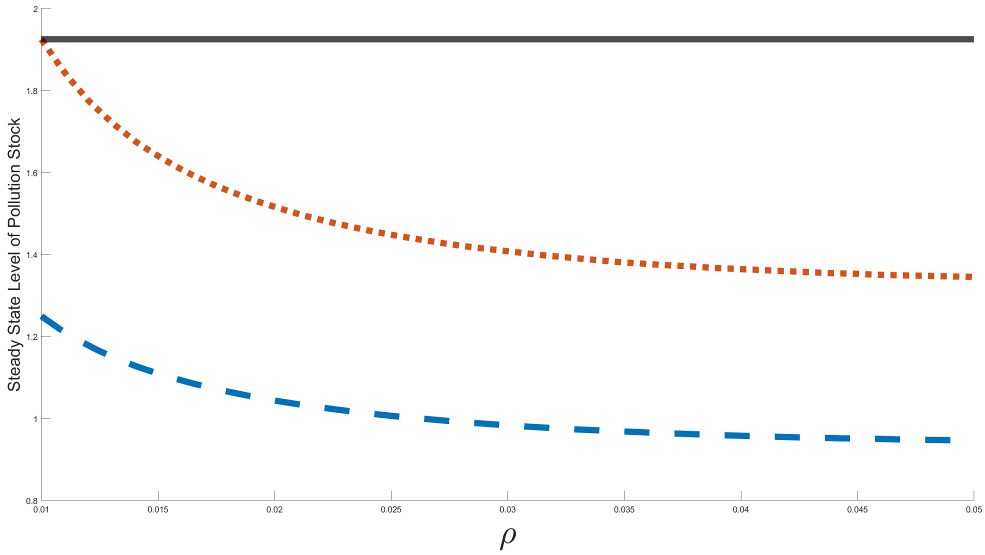

Figure 6: Steady state levels of pollution as a function of the discount factor ρ for the benchmark and full model pre- and post-shift, MPNE. The thick horizontal line gives the steady-state level of pollution post-shift. The dotted line gives the steady state level of pollution pre-shift for a model with mitigation and adaptation. The dashed line gives the steady state level of pollution pre-shift for a model with mitigation.

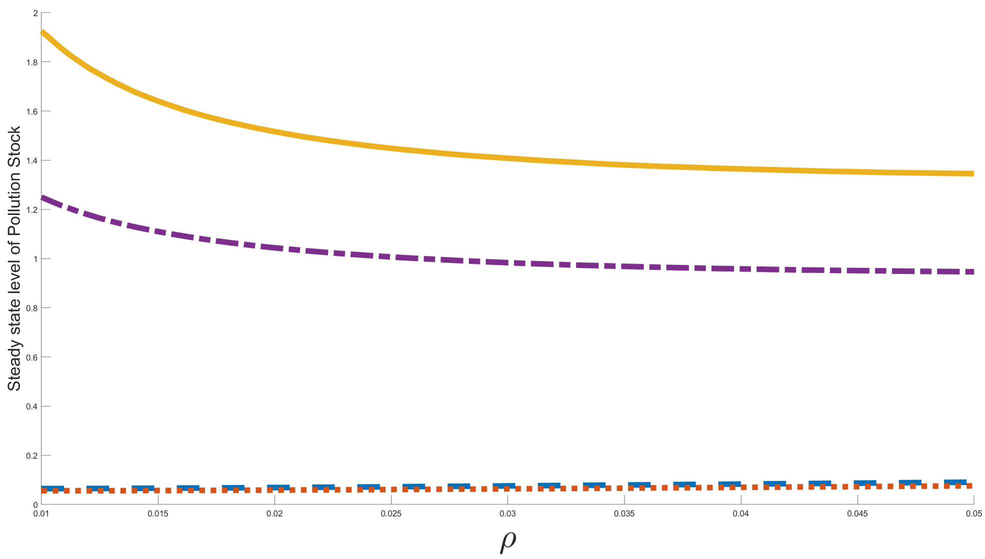

Figure 7: Gains from coordinating cooperation in pollution control for different levels of the discount factor ρ in four different model specifications. The dotted (dashed) lines correspond to the steady state level of pollution for a social planner model with mitigation (mitigation and adaptation) and the dashed-dotted (thick) lines correspond to the non-cooperative outcome with mitigation (mitigation and adaptation).

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