

Implications of a Lowered Damage
Trajectory for Mitigation
in a Continuous-Time Stochastic Model

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Abstract

This paper provides counterexamples to the idea that mitigation of greenhouse gases causing climate change, and adaptation to climate change, are always and everywhere substitutes. The author considers optimal policy for mitigating greenhouse gas emissions when climate damages follow a geometric Brownian motion process with positive drift, and the trajectory for damages can be down-shifted by adaptive activities, focusing on two main cases: 1) damages are reduced proportionately by adaptation for any given climate impact (“reactive adaptation”); and 2) the growth path for climate damages

is down-shifted (“anticipatory adaptation”). In this model mitigation is a lumpy one-off decision. Policy to reduce damages for given emissions is continuous in case 1, but may be lumpy in case 2, and reduces both expectation and variance of damages. Lower expected damages promote mitigation, and reduced variance discourages it (as the option value of waiting is reduced). In case 1, the last effect may dominate. Mitigation then *increases* when damages are *dampened*: mitigation and adaptation are complements. In case 2, mitigation and adaptation are always substitutes.

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**Implications of a Lowered Damage Trajectory for Mitigation
in a Continuous-Time Stochastic Model¹**

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1. Introduction

Two qualitatively distinct activities are induced by climate change: *mitigation* of greenhouse gases (GHGs) to limit emissions and thus future climate change; and *adaptation* to lessen the negative impact on human societies of any given climate change.² These activities are usually viewed as substitutes: more mitigation (leading to less GHG emissions) implies less climate change and thus less need to adapt; conversely, more adaptation reduces the damage from climate change, thus reducing the “need” to mitigate.³

For the effect of increased mitigation on adaptation, such a view appears robust. In this paper we are concerned with reverse relationships: *Given that the process for future damages resulting from given climate change is dampened or shifted down, what is the impact on optimal mitigation?* Increased adaptation to climate change is likely to reduce the damages to human societies for any given mitigation level, thus the two relationships may seem similar. But while much of adaptation activity is likely to come *later*, in *response to* given climate change, mitigation is always *anticipatory*, aiming to pre-empt anticipated but uncertain climate change.

The uncertainty part is here crucial. Two countervailing effects follow from more mitigation. First and most obviously, expected climate damages are reduced, which reduces the “need” to mitigate. But when adaptation causes the process describing climate damages to society to be dampened, uncertainty about future climate impacts (represented by the variance on the stochastic damage process) is also reduced.

This uncertainty is here modelled as a geometric Brownian motion process with positive drift. *Expected* damages from a given (increased) concentration of greenhouse gases (GHGs)

² When climate change results in welfare improvements, which is frequently the case, adaptation is the process by which these welfare gains are maximized.

³ See Tol (1998, 2005); Tol, Fankhauser and Smith (1998), Fankhauser, Smith and Tol (1999); Burton (1997). See also the wider discussion on interrelationship between mitigation and adaptation, in IPCC (2007).

are then assumed to increase over time. *Actual* damages are uncertain, and this uncertainty increases with the level of actual damages for given adaptation.

I study two cases. Both imply that the process for (unmitigated) damages is altered by policies that reduce climate damage (such policies are, commonly and imprecisely, denoted as “adaptation”). In the first case, the stochastic process for damages is “dampened”, meaning that actual damages are shifted down by a constant factor at all points in time. In this case there is no cumulative effect of the adaptive policy to reduce climate costs: all gains are *instantaneous*. In the second case, the process by which climate affects human societies is downshifted, in the sense that the constant positive drift on this process is dampened. Now there is a cumulative dampening effect on damages as it is the *expected rate of increase* for damages, per time unit, that is reduced. And unlike under case 1, there is no direct and immediate reduction in the uncertainty of the damage process.

Under both types of dampening of damages, both expectation and variance of climate damages are reduced. Pindyck (2000, 2002) and others have shown that when future climate damages are more uncertain, investments in “lumpy” mitigation activity involving large sunk costs (such as replacing coal-fired power plants with nuclear or renewable energy) are reduced, as the option value of waiting to invest increases.⁴ The intuition behind this result is that, under uncertainty, damages may turn out to be small; for such cases, the initial investment will be wasted. Waiting implies retaining the option to “wait and see” if damages will actually be so large that mitigation is worthwhile.

We study implications of each of the two types of “adaptive” measures for the timing of mitigation policy, which in our model takes a rather primitive, discrete and lumpy, form. We assume that authorities may make a major investment in new (energy or other) infrastructure investment that, after having been undertaken, removes all GHG emissions from the

⁴ See also Fisher (2000), Heal and Kriström (2002).

respective economic activity. The policy issue to be decided is when, if ever, this investment should be made.

In the first “adaptation” case, effects seem counterintuitive at first glance. For my first case (in section 3), under certain parametric conditions the reduced variance effect on mitigation timing, of the adaptation measure considered (which leads to sooner mitigation), dominates over the reduced expected damages effect (which leads to postponed mitigation). This increases the “propensity to mitigate” when damages are dampened, in the sense that the value for the stochastic variable, under which mitigation action is triggered, is reduced. In other words, *increased* (earlier) mitigation activity follows in cases where damages are *reduced*. I also show that the specified down-shift of the damage function may in fact be the result of optimal (“reactive”) adaptation given that the relationship between adaptive value and adaptation cost belongs to a particular, but I will argue plausible, class of functions (it is a function only of the ratio of adaptation costs to damages).

In the second case, treated in section 4, adaptation affects the positive drift of the damage process for given mitigation, but does not dampen the stochastic component as such. The results are then more standard: “more adaptation” now leads the decision maker to mitigate later on average, and a greater value of the continuous random variable is now necessary for mitigation to be triggered. It is more difficult to find an adaptation value function that fits to this case; also most reasonably, adaptation must now be “anticipatory”.

The final section 5 discusses these two cases further, in the context of more practical adaptation policy, and how such activity should most reasonably be interpreted in the two cases. I suggest that “adaptation policy” under case 1 should most readily be identified with “reactive” (ex post) adaptation (carried out by the public or private sector). Adaptation activity under case 2 is anticipatory, or perhaps what may be termed “climate-proofing”, whereby society is made more “robust” in meeting the challenge of higher global

temperatures. In this case adaptation modifies the impacts on society as if they were caused by lower temperatures.

2. Optimal Mitigation

This section closely follows Pindyck (2000). Define $M(t)$ as the stock of greenhouse gases (GHGs) in the atmosphere, and $E(t)$ as a flow variable that controls this stock. In the following, E is taken as the rate of emissions of GHGs, and can take a given number of nonnegative values. Assume that M is (deterministically) given from

$$(1) \quad dM(t) = [E(t) - \delta M(t)]dt ,$$

where δ is the rate of decay of the GHG stock. Associated with the stock variable M there is a flow variable of (negative) benefits, B , given by

$$(2) \quad B(M(t), \theta(t)) = -\mu(t)\theta(t)M(t).$$

θ is a multiplicative parameter governing the marginal cost to society from increasing the stock of GHGs. This parameter is stochastic and follows a geometric Brownian motion, on differential form described by

$$(3) \quad d\theta = \alpha\theta dt + \sigma\theta dz ,$$

where α is a (positive) drift parameter, and σ the standard deviation of the process.⁵

Considering a starting point θ_0 , at $t = T$ the logarithm of θ has expectation $(\alpha - \sigma^2/2)T$ and variance $\sigma^2 T$ (while θ itself has expectation αT).⁶

This process is modified by two types of policy interventions. The first of these is represented by μ in (2), which is assumed to take values less than or equal to unity. Assuming $\alpha > 0$, damages from a given concentration of GHGs in the atmosphere is systematically drifting upward over time, but with a random component that may make this upward drift highly uncertain. This process can be affected in three ways, one of which is associated with

⁵ See Dixit and Pindyck (1994), chapter 3, for a heuristic discussion of the formula and its applications; for more rigorous presentations see Harrison (1985), Karatzas and Shreve (1988), and Øksendal (2007).

⁶ See Dixit and Pindyck (1994), chapters 3-4.

mitigation policy, and the two others with “adaptation policy”. First, as studied by Pindyck (2000), the mitigation control parameter E can shift down to a new and permanently lower level, through (permanent) increased mitigation efforts, by incurring a cost K at the shift time. The two other types of policy intervention are new here. The first of these implies that the level of damages experienced by human societies, for given “climate impact” θ , can be affected by policy, and this is represented by a downward shift in μ . Such shifts work in two ways: it reduces both expectation and variance of the damage path. The final additional policy intervention is simply to (permanently) affect the drift rate α for the stochastic process for damages. In the following we will assume, alternatively, that the two latter policies are applied, exogenously, together with (endogenous, and optimal) mitigation policy: in section 3 we consider shifts in μ ; while in section 4, we assume that α shifts.

The policy objective W (at time 0) is

$$(4) \quad W = Exp(t = 0) \left\{ \int_0^{\infty} (-\mu(t)\theta(t)M(t))e^{-rt} dt - K(E_1)e^{-rT_1} \right\}$$

denoting welfare (or negative cost) associated with climate change, r being the discount rate. T_1 is the (uncertain, and endogenous) time of mitigation, modelled as a one-off decision. As in Pindyck (2000), mitigation costs take the simple form $K = kE$. We take expectations at time zero to indicate that T_1 is uncertain at $t = 0$. We will in the following also assume that μ is a constant, so that adaptation activity of the type studied in section 3 below, leads to a proportional downward shift in the damage level, independent of this level.

We now solve for the time of (possible) mitigation, T_1 , for given adaptation.⁷ This is a classical optimal stopping problem. Adopting a dynamic programming approach, we denote the value functions (4) for the pre-mitigation and post-mitigation states, by W^N and W^A respectively. Since the cost of adoption is linear in $E_0 - E_1$ (denoting the amount of mitigation

⁷ The second step of a full optimisation procedure, left for future research, would be to derive optimal adaptation, in the form of an optimal value or values of μ (section 3), or an optimal level of α (section 4).

achieved), there is nothing to gain by not reducing E to 0 once mitigating. Consequently, without loss of generality we assume that the amount of mitigation is E_0 , and that mitigation cost K equals kE_0 .

W^N and W^A must satisfy the Bellman equations (Pindyck (2000), equations (5)-(6)):

$$(5) \quad rW^N = -\mu\theta M + (E_0 - \delta M)W_M^N + \alpha\mu\theta W_\theta^N + \frac{1}{2}\mu^2\sigma^2 W_{\theta\theta}^N$$

$$(6) \quad rW^A = -\mu\theta M - \delta M W_M^A + \alpha\mu\theta W_\theta^N + \frac{1}{2}\mu^2\sigma^2 W_{\theta\theta}^N$$

where subscripts denote first- and second-order derivatives of the value functions. These must be solved simultaneously subject to the boundary conditions

$$(7) \quad W^N(0, M) = 0$$

$$(8) \quad W^N(\theta^*, M) = W^A(\theta^*, M) - kE_0$$

$$(9) \quad W_\theta^N(\theta^*, M) = W_\theta^A(\theta^*, M).$$

(7) states that the value (or climate cost) function must be zero with no current climate damages (and, with a geometric Brownian motion, never any climate damages). (8) defines the "stopping point" θ^* for θ (for mitigation), by indifference between action and non-action. (9) is the "smooth-pasting condition": the derivative of W must be continuous at the point of action, θ^* .

The solutions to (5)-(6) are

$$(10) \quad W^N = A(\mu\theta)^\gamma - \frac{\mu\theta M}{r + \delta - \alpha} - \frac{E_0\mu\theta}{(r - \alpha)(r + \delta - \alpha)}$$

$$(11) \quad W^A = -\frac{\mu\theta M}{r + \delta - \alpha}$$

where A and γ are constants to be determined. γ is the positive root of the quadratic equation

$$(12) \quad \frac{1}{2}\mu^2\sigma^2\gamma(\gamma - 1) + \mu\alpha\gamma - r = 0,$$

leading to the following solution for γ :

$$(13) \quad \gamma = \frac{1}{2} - \frac{\alpha}{\mu\sigma^2} + \sqrt{\left(\frac{\alpha}{\mu\sigma^2} - \frac{1}{2}\right)^2 + \frac{2r}{\mu^2\sigma^2}} > 1.$$

The parameter A , and the critical value θ^* beyond which mitigation action is taken, are determined from (8) and (9):

$$(14) \quad A = \left(\frac{\gamma-1}{k}\right)^{\gamma-1} [(r-\alpha)(r+\delta-\alpha)\gamma]^{-\gamma} E_0$$

$$(15) \quad \theta^* = \frac{1}{\mu} \frac{\gamma}{\gamma-1} k(r-\alpha)(r+\delta-\alpha).$$

Under full certainty, the critical value of θ triggering mitigation would be determined from

$$(16) \quad \theta^{**} = \frac{1}{\mu} k(r-\alpha)(r+\delta-\alpha).$$

Increased adaptation (reduced μ) increases θ^{**} proportionately to $1/\mu$, with a strong delaying effect on mitigation. This is intuitive: adaptation “takes over” the role of mitigation, making the latter less relevant and thus less urgent. Comparing (15) and (16), uncertainty increases θ^* relative to θ^{**} , by a factor $\gamma/(\gamma-1) > 1$ as $\gamma > 1$. In the set of cases where θ lies in the range (θ^{**}, θ^*) , there is then mitigation under certainty, but not under uncertainty.

3. Changes in Adaptation Policy 1: Shifts in μ

We now introduce “adaptation” policy in the form of shifting μ downward, to study its effects on optimal mitigation under uncertainty (for cases where γ takes a finite positive value greater than unity). Under certainty, this is a trivial problem: from (16), $\mu\theta^{**}$ is a constant, and lower μ leads to a proportional increase in θ^{**} ; and to mitigation being postponed. Under uncertainty the situation is more complex as also γ is affected by changes in μ . $\Gamma = \gamma/[\mu(\gamma-1)]$ is then the relevant measure. Note that $\gamma/(\gamma-1)$ drops in γ (when, as here $\gamma > 1$). If γ increases when μ drops, the option value of waiting is then also reduced. Even stronger, when $\gamma/(\gamma-1)$ is reduced more than μ , θ^* drops when μ drops: increased adaptation then raises mitigation.

Taking the derivative of γ with respect to μ in (13):

$$(17) \quad \frac{d\gamma}{d\mu} = \frac{\alpha}{\mu\sigma^2} - \left(\left(\frac{\alpha}{\mu\sigma^2} - \frac{1}{2} \right)^2 + \frac{2r}{\mu^2\sigma^2} \right)^{-\frac{1}{2}} \left[\left(\frac{\alpha}{\mu\sigma^2} - \frac{1}{2} \right) \frac{\alpha}{\mu^2\sigma^2} + \frac{4r}{\mu^2\sigma^2} \right].$$

Consider a small change in μ starting from $\mu = 1$ (no adaptation). (17) can be written

$$(18) \quad \frac{d\gamma}{d\mu} = \frac{\alpha}{\sigma^2} \left[1 - \left(\left(\frac{\alpha}{\sigma^2} - \frac{1}{2} \right)^2 + \frac{2r}{\sigma^2} \right)^{-\frac{1}{2}} \left(\frac{\alpha}{\sigma^2} - \frac{1}{2} + \frac{4r}{\alpha} \right) \right].$$

Here $d\gamma/d\mu < 0$ in a wide range of circumstances. A more crucial question for us is whether the increase in γ can be sufficiently great that $\gamma/(\gamma-1)$ drops by more than the initial drop in μ .

We find

$$(19) \quad \frac{d\left(\frac{\gamma}{\gamma-1}\right)}{d\mu} = - \left(\frac{1}{\gamma-1} \right)^2 \frac{d\gamma}{d\mu},$$

where $d\gamma/d\mu$ is found from (18). Thus when γ is close to unity and at the same time $d\gamma/d\mu < 0$, $\gamma/[\mu(\gamma-1)]$ drops when μ drops. Increased adaptation will then lead to “more mitigation”, in the sense that the (one-off) mitigation investment is incurred earlier.

To exemplify, consider the case $\alpha/\sigma^2 = 1/2$ (when, following Dixit and Pindyck (1994),

$E_{t=0}[\log \theta(\tau)] = \log \theta(0)$; even though $E_{t=0}[\theta(\tau)] = \theta(0) + (\alpha\tau)$).⁸ We find:

$$(20) \quad \frac{d\left(\frac{\gamma}{\gamma-1}\right)}{d\mu} = \left(\left(\frac{r}{\alpha} \right)^{\frac{1}{2}} - 1 \right)^{-2} \left(\left(\frac{r}{\alpha} \right)^{\frac{1}{2}} - \frac{1}{4} \right).$$

$r > \alpha$ is here a requirement for θ^* to be finite. Whenever α is then “not small” relative to r , the expression on the right-hand side of (20) exceeds unity; required for a drop in μ to lead to a drop in θ^* . The more precise condition is found as $\alpha \geq (4/25)r$ (by setting the right-hand side

⁸ Note however that this case is in itself not useful for deriving optimal expected times until mitigation intervention, since in this case, this expected period is infinite; see section 4 below. This case is useful only as a benchmark and for its simplicity of illustration (and, invoking continuity, by showing that a similar result will hold also for more interesting cases involving $\alpha > \sigma^2/2$).

of (20) equal to unity, and solving this as a quadratic equation in $\sqrt{r/\alpha}$. This seems as a not very restrictive condition.

Can the indicated adaptation response to given damages, implied by this version of the model, correspond to optimal adaptation? To answer this question, consider a case where adaptation is completely reactive, following in response to given damages (so that no anticipatory adaptation is in question). We seek an adaptation cost function that fits case 1, where a basic presumption is that damages are dampened by adaptation, proportionately to the initial level of damages. A class of adaptation value functions that fits to these assumptions is one where optimal gains from and costs of adaptation are both proportional to the initial level of damages. A suitable net value function (for the value, net of adaptation costs, of incurring the adaptation cost A given an instantaneous climate damage level D) has the form

$$(21) \quad V = \beta \left(\frac{A}{D} \right) D - A ,$$

where β is a positive-valued function with first- and second order derivatives, $\beta' > 0$, $\beta'' < 0$, $\beta(0) = 0$, $\beta(\infty) = 1$. V is maximized with respect to A , yielding

$$(22) \quad \frac{dV}{dA} = \beta' - 1 = 0 \Leftrightarrow \beta' = 1 .$$

(22) yields a unique solution for β , call it β^* , and consequently a unique solution for $A/D = \gamma$, call it γ^* . Net climate damages, net of adaptation gains and costs, can now be written $D - \beta^*D + \gamma^*D = (1 - \beta^* + \gamma^*)D$, where both β^* and γ^* constants, and where $0 < \beta^* - \gamma^* < 1$. Thus $(1 - \beta^* + \gamma^*)$ is a positive constant less than unity, independent of the damage level D , and corresponds to the coefficient μ in the analysis in this section. It is clear that this type of adaptation is “reactive”, carried out in response to the particular level of damage occurring, at any given time.

When the function β takes the particular Cobb-Douglas form, (21) can be written as

$$(23) \quad V = \left(\frac{A}{D} \right)^\varepsilon D - A,$$

where ε is the elasticity of “adaptive value” with respect to adaptation costs, and where $0 < \varepsilon < 1$. In this case,

$$(24) \quad \mu = 1 - \beta^* + \gamma^* = 1 - (1 - \varepsilon)\varepsilon^{\frac{\varepsilon}{1-\varepsilon}} < 1,$$

where μ is a constant. A negative shift in ε is here tantamount to a negative shift in μ .

4. Changes in Adaptation Policy 2: Shift in α

My second case of “adaptation policy” involves down-shifting the drift parameter α of the stochastic process for θ . The main interpretation of such policy might seem to be one of (more efficient) mitigation, insofar as θ describes the process by which climate is altered. However, an interpretation could equally well be that society, for given climate as represented by a basic (non-shifted) stochastic damage process θ , is affected by climate in the same way as if θ were down-shifted. One way to view such a shift is that society is made more resilient in the face of climate change. This also gives room for an interpretation in terms of “adaptation”; and now most reasonably anticipatory adaptation or “climate proofing”.

An immediate issue for this case is that when α is reduced, the expected time until mitigation, τ , increases for given θ^* . The formula for this expected time is⁹

$$(25) \quad E(\tau; \theta^*, \theta_0) = \frac{\log\left(\frac{\theta^*}{\theta_0}\right)}{\alpha - \frac{\sigma^2}{2}}.$$

The expected time until mitigation, $E(\tau)$, is here finite only when $\alpha > \sigma^2/2$.¹⁰ Given this inequality, $E(\tau)$ is a negative function of α so that a reduced α leads to a higher $E(\tau)$. Thus,

⁹ See Øksendal (2007), p 131.

when a reduced α is interpreted as “better adaptation” or “climate-proofing” (as argued below), this in itself delays mitigation as it simply reduces the “perceived need” to mitigate. This is a feature that was not present in our case 1.

We are next interested in how θ^* is affected by changes in α . Note again that a lower α implies that damages are reduced at all future points of time, and thus the cumulative damaging effect of current emissions reduced. This feature tends to raise the optimal value of θ . But also here we find a negative effect on the variance and thus the option value of waiting for any given θ . Another major difference from case a above is that the expected time it takes to reach a given θ now increases (as the very process for θ is downshifted).

In this case, the derivative of θ^* with respect to α is found as

$$(26) \quad \frac{d\theta^*}{d\alpha} = -\frac{k}{(\gamma-1)^2} \left\{ \frac{(r-\alpha)(r-\alpha+\delta)}{\sigma^2} \frac{d\gamma}{d\alpha} + \gamma(\gamma-1)(2(r-\alpha)+\delta) \right\},$$

where

$$(27) \quad \frac{d\gamma}{d\alpha} = -\frac{1}{\sigma^2} \left\{ 1 - \left(\frac{\alpha}{\sigma^2} - \frac{1}{2} \right) \left[\left(\frac{\alpha}{\sigma^2} - \frac{1}{2} \right)^2 + \frac{2r}{\sigma^2} \right]^{-\frac{1}{2}} \right\}.$$

The first main term in the curled bracket in (26) can be interpreted as the effect of reduced uncertainty (variance) of damages when α is reduced; while the second term can be interpreted as the effect of reduced expected damages. As in section 3 the variance term works to increase θ^* , and the expectation term to reduce it.

Can we here find cases where $d\theta^*/d\alpha > 0$? The first main term in the curled bracket in (26) (the “variance term”) would then need to dominate the second term (the “expectation term”). This is however not the case here: for all valid parameter combinations, $d\theta^*/d\alpha < 0$. Thus the

¹⁰ Note that even when $\alpha < \sigma^2/2$, τ is finite with positive probability (that increases in $\alpha - \sigma^2/2$), applying Dynkin’s (1965) formula; and infinite with the complementary probability; thus $E(\tau)$ is infinite: see also Øksendal (2007), p 131. Thus τ can be finite in “many” cases, and with probability mass that approaches 1 as $\alpha - \sigma^2/2$ approaches zero from below.

relationship between mitigation and adaptation is “traditional”: more adaptation reduces the “need” for mitigation in the sense that the trigger value for the stochastic variable θ , beyond which mitigation is triggered, is now increased when α drops (“more climate proofing”). There is a double such effect, since the time it takes to first reach *any given* level of θ is now longer in expectation, from (25).

Finally, what if any adaptation or cost function produces this type of adaptation response? One obvious candidate is an investment sunk early on, which leads to permanent effects directly on the growth trajectory. Such an investment would constitute “anticipatory adaptation”, but might in some contexts perhaps be indistinguishable from mitigation policy.

5. Discussion

I have in this paper studied whether policies to reduce GHG emissions (mitigation), and policies to reduce damages caused by climate change (“adaptation”), are everywhere and in all circumstances “*substitutes*” (so that applying more of one policy makes it optimal to apply less of the other), in the context of a particular model by which climate damages develop according to a continuous-time Brownian motion process with drift. I present a practical counter-example to this principle, where policies to reduce GHG emissions (mitigation), and particular policies to reduce the damages caused by climate change (“adaptation”), are *complements*. This possibility exists under uncertainty because “adaptation” broadly can take two different forms. Complementarity between mitigation and adaptation can be the outcome when damages caused by climate change are down-shifted proportionately by “reactive adaptation”. From our model such an argument, and the intuition behind it, fails in some cases when the “option value” associated with waiting to implement mitigation policy is substantial.

The “option value” is due to uncertainty about future climate damages, and how this uncertainty evolves over time. Large uncertainty implies that climate (including the damage

that it causes) may become worse; but could also improve. The possibility that it can improve “substantially” from today’s level and into the immediate future is greater, the greater is the uncertainty of the stochastic underlying variable controlling climate damages. A policy to reduce this uncertainty reduces the incentive to wait “a little” for possible better times in the “very near” future, and instead implement the relevant mitigation policy immediately. The key point we emphasize in our presentation is that this uncertainty effect may dominate over the effect of reduced expected damages (which, in isolation, leads to mitigation being postponed). In consequence we have the paradoxical situation that “more adaptation” implies “more mitigation”: the value for a stochastic damage variable that triggers mitigation policy shifts down: mitigation is carried out “earlier”.

In analyzing this model, we focus on two distinct interpretations of the role of adaptation policy, as two different forms that multiplicative downward shifts in net climate damages may take. In either case, the climate damage trajectory under “business-as-usual” mitigation policy is assumed to follow a geometric Brownian motion process with constant positive drift. In the first case, *damages resulting from a given climate change are dampened*, by “adaptation”. This is perhaps the most straightforward interpretation of adaptation; it can in principle be interpreted as either reactive or anticipatory adaptation, but most reasonably as the former. The policy behind this effect reduces climate damages proportionately in all states. In section 3 we discuss conditions under which the assumed, proportional, dampening of the stochastic damage process can be a result of optimal (reactive) adaptation. I show that this is the case when both the degree to which climate damages are mitigated by reactive adaptation, and adaptation costs, rise in exact proportion to damages. I also provide a concrete example in terms of a Cobb-Douglas “damage mitigation function”.

In our alternative case, “adaptation” is interpreted as modifying the (damage-related) climate impact, so that the rate of drift of the stochastic process for damages is shifted down. I

then find nothing unusual or surprising. “More adaptation” then always reduces mitigation, in two distinct ways: the point of time at which mitigation is executed is delayed for given value of the stochastic parameter governing climate damages; and the value of the stochastic variable that triggers mitigation is higher. This may, arguably, correspond to “climate-proofing” whereby society is made better able to withstand given changes in climate. It is here also easier to visualize the types of impact that our form of “climate-proofing” may have; in particular, it may, as in our model, be a cumulative process whereby “layers” of climate-proofing may gradually add to the overall resiliency of society. Again, this view is speculative and needs confirmation through subsequent research.

Why is there a difference in outcome between our two examples? In the first case, the *level* as well as the *variance* on damages are affected *directly and immediately*. In the second case there is only an *indirect* effect as the stochastic process for damages and its variance are not affected immediately. Such effects only come later (from the process being down-shifted and a geometric uncertain component). The option value is affected more directly, and by relatively more, in the first case than in the second. Intuitively, the short-run reactive type of adaptation that reduces the (short-run) uncertainty the most. Note here that the option value concept is essentially one of (very) short-run maximization: should one wait one further instant to mitigate, or should one do it now. Such tradeoffs are affected much less by our “climate-proofing” policy, where it is the long run that is on the whole affected.

In terms of policy implications, it is of course desirable that climate damages can be down-shifted. It may then be useful to know that such a down-shift may, sometimes, make also more mitigation attractive, so that adaptation and mitigation activity would tend to reinforce each other. But it is important to stress that this outcome follows from a particular and perhaps not very general example; such an outcome can thus not be taken for granted.

Strong assumptions lie behind this analysis, and these may need relaxation in future work. First, decision makers (governments) are considered risk neutral. Risk aversion would tend to reduce the option value of waiting (in particular, highly positive future outcomes are given less weight); although the overall effect of this remains unclear. Secondly, adaptation and mitigation are given stylised and abstract interpretations. Mitigation is “one-off”: to mitigate all GHG emissions, or nothing. It remains to be seen whether more realistic assumptions can be accommodated without jeopardizing main conclusions. Pindyck (2000, 2002) has considered partial mitigation in a similar set-up, with similar qualitative results. It neither appears crucial that all mitigation costs are sunk and paid up-front. A fixed cost component is crucial; if not, the option value argument, crucial for our results, fails. Thirdly, adaptation is modelled in very simple ways, as a constant multiplicative modification of the damage path, or as a modification of the rate of change of the stochastic process causing climate change damages.

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