Optimal control models and elicitation of attitudes towards climate damages

Philippe Ambrosi[a*], Jean-Charles Hourcade[a], Stéphane Hallegatte[a], Franck Lecocq[b], Patrice Dumas[a], Minh Ha Duong[a]

a*: CIRED, Jardin Tropical, 45bis avenue de la Belle Gabrielle, F-94 736 Nogent-sur-Marne, France*

b*: World Bank, Development Economics Research Group, 1818 H St. NW, Washington D.C., USA*

forthcoming in *Environmental Modeling and Assessment*
special issue on "Modeling the economic response to global climate change"

Abstract: This paper examines the consequences of various attitudes towards climate damages through a family of stochastic optimal control models (*RESPONSE*): cost-efficiency for a given temperature ceiling; cost-benefit analysis with a "pure preference for current climate regime" and full cost-benefit analysis. The choice of a given proxy of climate change risks is actually more than a technical option. It is essentially motivated by the degree of distrust regarding the legitimacy of an assessment of climate damages and the possibility of providing in due time reliable and non controversial estimates. Our results demonstrate that a) for early decades abatement, the difference between various decision-making frameworks appears to matter less than the difference between stochastic and non stochastic approach given the cascade of uncertainty from emissions to damages; b) in a stochastic approach, the possibility of non-catastrophic singularities in the damage function is sufficient to significantly increase earlier optimal abatements; c) a window of opportunity for action exists up to 2040: abatements further delayed may induce significant regret in case of bad news about climate response or singularities in damages.

keywords: cost-efficiency, cost-benefit, climate sensitivity, climate change damages, uncertainty, optimal climate policy, decision making frameworks.

[*] corresponding author. e-mail : ambrosi@centre-cired.fr; tel : +33 1 43 94 73 87 ; fax : +33 1 43 94 73 70.

1. Introduction

Little progress has been made since 1992 on what constitutes a "*dangerous anthropogenic interference with the climate system*" [1]. The Third Assessment Report (TAR) of the Intergovernmental Panel on Climate Change (IPCC) delivered new material on climate change impacts but did not venture to deliver any conclusive judgment [2]. In this context, which decision-making framework should be used to design climate policies remains an open question (see [3] (chap. 1&2) and [4] (chap. 10) for a survey). Bounded cost; minimax regret; maximin gain; minimax loss; cost-effectiveness, tolerable windows and safe landing approaches; cost-benefit analysis, each with its own merits and limitations, are representative of the diversity of decision-making attitudes in a *sea of uncertainty* [5].

The objective of this paper is to assess how each of these attitudes translates in terms of timing of emissions abatement. It is achieved through the use of optimal control models, which can put some rationale into pending controversies and thus facilitate the emergence of compromises because they are apt to disentangle the sources of misunderstandings from the real division lines. Indeed they force the analyst to a) identify the pathways through which climate change may impact on global welfare; b) clarify the proxies that are used to capture the benefits of climate action, and against which the costs of this action are to be weighted and c) make explicit the level of confidence about scientific information and the ethical choices which underpin the selection of a given framework. Hence, after having discussed (section 2) how various attitudes towards climate change lead to various metrics to capture the benefits of climate policies we successively analyze the optimal abatement pathway derived from (section 3) a cost-effectiveness analysis of temperature ceiling objectives, (section 4) a cost-benefit analysis using a pure preference for current climate regime and (section 5) a cost-benefit approach using a monetized quantification of damages.

2. Metrics for assessing benefits of climate policies

IPCC TAR indicates that global mean temperature is projected to increase by 1.4 to 5.8°C over the period 1990 to 2100 as a consequence of greenhouse gases anthropogenic emissions.

Faced with such a large uncertainty range, debates about the application of the Precautionary Principle come to select specific metrics of the benefits of climate policies. The selection of such metrics is certainly motivated by value judgments, but it is not independent from the degree of distrust regarding the possibility of timely providing reliable and non controversial estimates. Attitudes can be grouped into three broad categories:

a) A first one considers that the uncertainty about climate impacts and damages is so high that they cannot be confidently assigned any numerical value; environmental benefits are thus set in the form of arbitrary ceilings on either greenhouse gases (GHGs) concentration, temperature, or any other multidimensional indicator. Approaches such as a safe corridor, a safe landing or a viability path also belong to this cost-efficiency framework; their outcome depends obviously on whether the constraints are set by a *convinced ecologist* or by a *skeptical ecologist* (*à la* Lomborg). Sharing the same distrust about predictions of climate impacts, the convinced and the skeptical ecologist may search for a *reasoned compromise*, and agree on a sequential decision-making process in which an initial trajectory can be adapted in the light of new information. This common will to consider several conceivable futures and to keep open alternative options leads to substitute a stochastic to a deterministic cost-efficiency model.

b) Another attitude refuses the arbitrary setting of absolute targets and demands a cost-benefit analysis; however, being skeptic about explicit prediction and assessment of damages, it does not use an itemized assessment of these damages but a willingness to pay for avoiding various levels of climate change. In modeling terms, this is translated through the inclusion of climate change indicators (temperature or rainfall patterns, extreme events) in the utility function to express a *pure preference for current climate regime (PCCR)*. This PCCR conveys precautionary ethics leading to favoring the current climate regime over unknown alternatives; it incorporates psychological motivations about endangered habitats, the amenity or bequest value of landscapes, all values considered a part of climate policy benefits in the absence of definition of climate feedbacks on economic productivity. Depending on the specification of the utility function, the environment appears (or does not appear) as a superior good (a good to which agents dedicate a growing share of their income as they become richer).

c) The last attitude leads also to the carrying out of a cost-benefit analysis but requires an itemized monetary assessment of impacts. This assessment confronts uncertainty of impact predictions and raises controversies[1] about monetary valuation (such as placing a monetary value on human life in different countries or aggregating regional estimates assuming a compensation hypothesis). Many perform such an assessment though, for lack of anything better, to place some rationale into policy debates about long term targets, be it to convince public opinion to accept subsequent unpopular measures or to resist disproportionate demands from environmentalists.

Hence, the choice of a metrics of the benefits from mitigation policies is actually much more than a mere technical option. It reflects a judgement on the quality of the available information and on its ability to serve as a common basis in the negotiation process. In other words, it implies a trade-off between accuracy and relevance [8]: accuracy because the further *down* we move along the causal chain linking GHGs emissions to climate change damages, the less confidence we place in our ability to predict the outcome of the cascade of uncertainties we are faced with; relevance because the further *up* we proceed from damages functions to GHGs concentrations ceilings, the further we get from a precise description of climate change consequences, in particular with regard to welfare and distributive aspects.

To compare the policy implications of these attitudes, we have performed a set of harmonized numerical experiments based on the *RESPONSE* model family. *RESPONSE* is an aggregate optimal control integrated model which include reduced forms of carbon cycle and climate dynamics. Using a sequential decision-making framework, we focus on the sensitivity of first period decisions to the combination of uncertainties about climate change consequences, and to the choice of one of the three metrics described above.

These experiments have been conducted for a single baseline growth scenario (the marker of A1 SRES) and set of abatement cost curves. The specification of the abatement cost function is meant to capture the role of socio-economic inertia as a cost multiplier; it incorporates an autonomous technological change factor (see Appendix A).

[1]For instance, the forum on valuation of ecosystem services (*Ecological Economics*, 1998. 25(1)) which has been emulated by Costanza on the basis of [6]. Many respondents have indeed pointed out the risk of underestimating the environment as Toman [7] elegantly puts it: “a serious underestimate of infinity”.

The objective functions only differ among variants of the model:

- *RESPONSE_T* (T for temperature) explores the first attitude and minimizes the discounted sum of abatement costs with respect to an environmental constraint on global mean temperature rise;
- *RESPONSE_P* (P for preference for current climate regime) explores the second attitude and maximizes the intertemporal welfare derived from both consumption and the amenity value of climate;
- *RESPONSE_D* (D for damages) explores the third attitude and maximizes the intertemporal welfare derived from consumption minus abatement expenditures and resulting damages.

General specifications of *RESPONSE* will be introduced in the following section with the description of *RESPONSE_T* (both in deterministic and stochastic versions); for the remaining sections, we will solely describe the specific differences (with respect to the generic model) of the version we refer to.

3. Lessons from a stochastic cost-efficiency analysis: *RESPONSE_T*

Up to Kyoto, efforts to clarify controversies about the timing of GHGs abatements have been conducted through a cost-efficiency analysis within a sequential decision framework enabling to adjust an initial response in the light of new information [9]. Whereas a delay in the bulk of abatement efforts is justified if a given GHGs concentration target is known in advance [10], an earlier and higher departure from baseline emissions trends is required if the same, say 550 ppm target, is considered as the mean of three yet unknown values (say 450 ppm, 550 ppm and 650 ppm) and if information about the real value is expected to be disclosed some decades in the future [9]. Two main results emerge from this analysis which remain relevant whatever the attitude towards climate risks:

a) the role of the interplay between uncertainty about the ultimate target and the inertia of technical and environmental systems: without inertia, transition costs of switching from one emission path to another would be null, and uncertainty would not matter; in fact, inertia raises both the costs of premature abatement and that of accelerated abatement if stronger action is called for later;

b) the value of the discount rate matters less than 1) the set of probabilities placed on the targets, and, more specifically the weight given to the tightest one and 2) the date of resolution of uncertainty: the later this uncertainty is to be resolved, the earlier the abatement efforts have to be scheduled.

Whereas a cost-efficiency analysis of concentration ceilings is policy relevant because it follows the very language of the UNFCCC, it is a poor proxy of the benefits of climate action. More specifically it does not allow for considering the uncertainty regarding climate sensitivity. This parameter is defined as the global mean surface temperature increase at the equilibrium, when CO_2 concentration is kept constant at twice the pre-industrial level. Literature sets this parameter between +1.5 °C and +4.5°C [11] (chp. IX).

This is why it is attractive to carry out a cost-efficiency analysis of temperature ceilings. *RESPONSE_T* performs such an analysis through an objective function (1a) minimizing the discounted sum of abatement costs (a surrogate of a utility-maximization model where consumption is lowered by mitigation measures), with as environmental constraint (1b) a ceiling on the global mean temperature rise relative to its 1990 value.

$$\underset{Ab_t}{Min} \sum_{t=1990}^{2300} \frac{f(Ab_t, Ab_{t-1}, t)}{(1+\rho)^{(t-1990)}} \quad (1a)$$

$$w.r.t. \quad \left(\theta_t - \theta_{1990}\right) \leq \Delta\theta_{MAX} \quad (1b)$$

with: *f(.)* the abatement cost function
Ab_t the abatement rate at time *t* (% of baseline emissions)
ρ the discount rate (5%.year^{-1})
θ_t the global mean temperature rise at time *t*
$\Delta\theta_{MAX}$ the constraint on global mean temperature rise relative to 1990

The carbon cycle (2) is taken from William Nordhaus [12]: it is a linear three-reservoir model which describes carbon accumulation and transportation between the atmosphere, the biosphere (oceanic and continental) and deep ocean. The model accounts for some inertia in natural processes. Related parameters (transfer coefficients and initial conditions) are given in Appendix A.

$$M_{t+1} = C_{trans}.M_t + \delta\,(1 - Ab_t)em_t.u \quad (2)$$

with: M_t the carbon contents of each reservoir at time *t*, a column vector
C_{trans} the net transfer coefficients matrix, a 3x3 matrix
δ the time step of the model (10 years)
em_t the baseline carbon dioxide emissions at time *t*, exogenous (A1-m scenario)
u a column vector (1,0,0)

Lastly, variations in global mean temperature derive from a two-box climate model (3) describing the modification of the thermal equilibrium between atmosphere and ocean in response to enhanced greenhouse effect (carbon dioxide only) based on specifications close to Nordhaus's one [12]. To improve the quality of the insight on the timing of abatement over the short run, we calibrated this model in such a way that it gives a better description of warming over forthcoming decades: we prioritize the description of the interaction between the atmosphere and the superficial ocean neglecting interactions with the deep ocean. A thorough description is provided in appendix A.

$$\theta_{t+1} = L(\theta_t, M_t) \quad (3)$$

The model defined by equations (1), (2) and (3) can be run on a perfect information mode (*RESPONSE_T/c*) and on an uncertainty mode (*RESPONSE_T/s*). In the second option, uncertainty on climate sensitivity is discrete : we consider three possible states of the world (s) in which climate sensitivity may be {2.5°C;3.5°C;4.5°C} with the corresponding *ex ante* subjective probabilities (p_s) {1/6;2/3;1/6}. Information arrives at a fixed time in the future (t_{info}). The program solves a set of three parallel problems – three equations (2) and (3) representing three alternative states of the world; climate dynamics (3) is notably dependent on the value of climate sensitivity. The objective function (1a) is re-specified as the minimization of expected costs of abatement paths:

$$\underset{Ab_t^s}{Min} \sum_s p_s \sum_{t=1990}^{2300} \frac{f(Ab_t^s Ab_{t-1}^s, t)}{(1+\rho)^{(t-1990)}} \quad (1a)$$

Environmental constraint (1b) is rewritten to consider each state of the world:

$$w.r.t. \quad \left(\theta_t^s - \theta_{1990}\right) \leq \theta_{MAX} \quad (1b)$$

Additional constraints (1c) are added to impose that, before the disclosure of information, decision variables be the same across all states of the world:

$$\forall t \leq t_{info},\ \forall\left(s, s'\right) \in S,\ Ab_t^s = Ab_t^{s'} \quad (1c)$$

Model solutions correspond technically to perfect information when t_{info} =1990, imperfect information with learning when (1990<t_{info} <2300), absolute uncertainty when t_{info} =2300.

Let us start from a +2°C target[2] with respect to 1990. It corresponds to an expected value of 500 ppm for GHGs concentration, actually shifting from a very stringent 440 ppm when climate sensitivity is set to its upper value to a very lax 590 ppm when climate sensitivity is at its lower value. A +1°C and +3°C target would respectively lead to a 379-448 ppm range (expected value: 408ppm) and to a 515-780 ppm range (expected value: 617ppm) for concentration ceiling.

It appears that for a +2°C target, and assuming that information on the value of climate sensitivity arrives in 2020, the earlier periods optimal emissions path is very close to the one consistent with the most pessimistic hypothesis about this value (Figure 1). When compared with results obtained with GHGs concentration ceilings, the dominance of the worst case hypothesis is reinforced: pessimistic assumptions regarding climate sensitivity lead to a tighter constraint (440 ppm) and, more importantly, implie that the + 2°C temperature ceiling is reached as early as 2050 in the baseline case. Consequently, the model accounts for the fact that any delay in climate policy will result in a costly acceleration of GHG abatement.

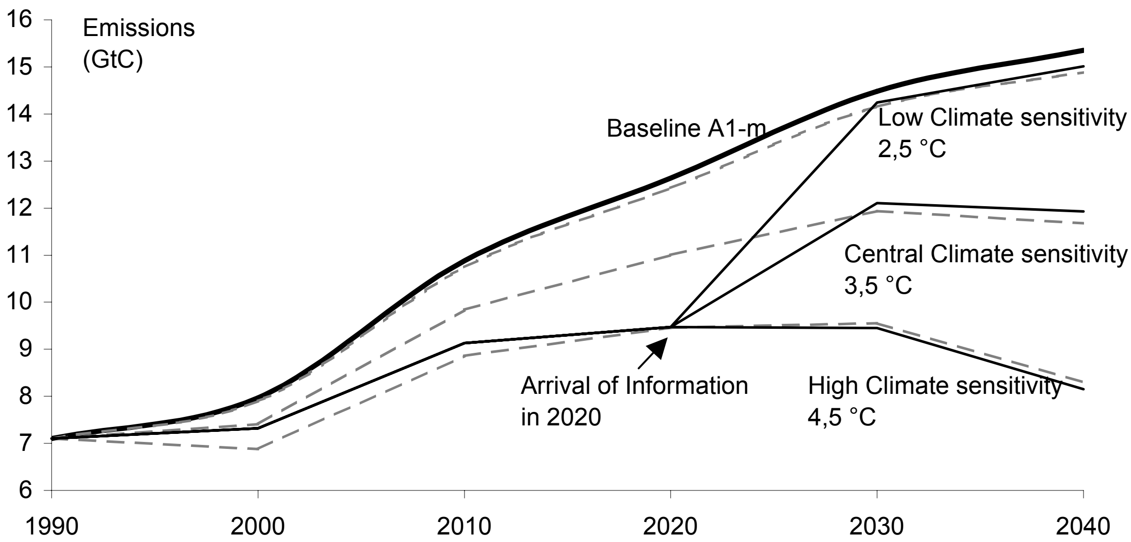

Figure 1: Hedging strategies for a given +2°C temperature ceiling : with perfect information (grey dashed line) and with uncertainties (black continue line).

A good indicator of the environmental irreversibility is captured by the value of information on climate sensitivity. The Expected Value of Perfect Information (EVPI) is classically the difference between the expected value of the objective function in the “Learn then Act” (climate sensitivity known from the outset and policy adopted consequently) and in the “Act then Learn” (a policy must be adopted before the value of this parameter is revealed) [16]. Logically, the later the date of resolution of uncertainty the higher the EVPI. Before 2040

[2] This figure is circulated in many studies such as the Global Fast Track Assessment [13] where the additional number of people at risk of water shortage increases sharply once global mean temperature rise gets close to +2°C. [14] also suggests that a +2°C temperature increase dramatically reduces suitable areas for Robusta coffee in Uganda. Note that this target is less binding than former EU long-term climate goals [15], amounting to a maximum +2°C global mean temperature rise *wrt preindustrial level*.

(Figure 2), it increases linearly up to 13% of its final value and then sharply between 2040 and 2070 to reach 83% of this value. To give a comparative benchmark, the expected value of discounted abatement costs over the three states of the world in the Learn then Act hypothesis would amount almost to 52 percentage points in the same metrics. Such a high opportunity cost of knowing climate sensitivity before 2040 highlights the risk of postponing too much a serious hedging strategy in case of pessimistic prospects about the progress in scientific knowledge and public awareness of climate risks

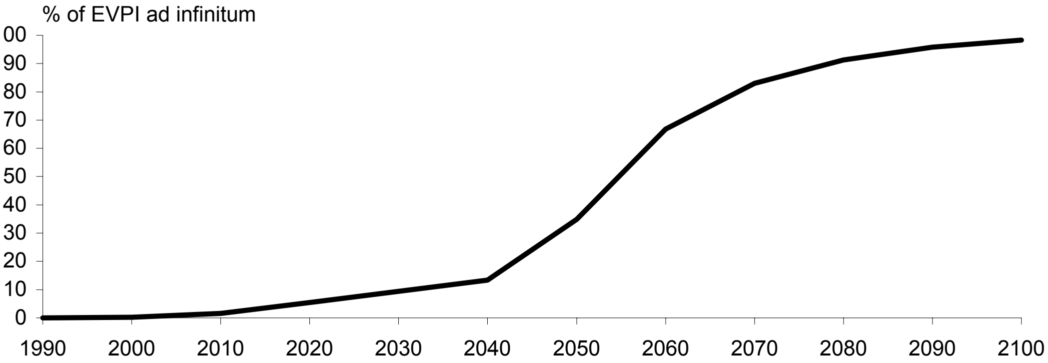

Figure 2 : Expected Value of Perfect Information with respect to the date of resolution of uncertainty on climate sensitivity. Information value raises brutally after 2040, that means there is a significant interest in revealing this value before this date [17].

The main criticism addressed to a stochastic cost-efficiency analysis is that it gives too high a weight to the tightest constraint. The set of probabilities can be indeed interpreted either in terms of subjective probabilities or in terms of shares in a population of subgroups advocating for a given constraint. In the latter case the program comes to find a compromise between competing views of the world. But a minority, say a fringe of 10% of the population, arguing for a 390 ppm target, would automatically exert a disproportionate influence on decision because costs of postponing action for this target tend towards infinity.

In practice though, faced with such a situation, societies would overshoot the ceiling at the risk of some damages admitting that a window of opportunity has been missed [18], rather than bear the social costs of an exaggerated deceleration of emissions. The necessity of examining such trade-off is the main argument for shifting from cost-efficiency analysis to some form of cost-benefit approach.

4. The Pure Preference for the Current Climate Regime: *RESPONSE_P*

As explained in section 2, the first form of cost-benefit analysis, consistent with an attitude of distrust regarding any numerical assessment of damages, considers a willingness to pay for mitigating climate change and a *pure preference for current climate regime* (PCCR).

Let U(.) denote the utility function. C_t denotes current consumption level; climate change is expressed by global mean temperature rise, θ_t. We specify U(.) such as $U(C_t,\theta_t) = \ln(C_t).(\bar{\theta} - \theta_t)^{\beta}$ with 0 < (1<)C_t and $\theta_t < \bar{\theta}$, $0 < \beta < 1$. $\bar{\theta}$ denotes an absolute threshold beyond which climate change impacts would be overbearingly disruptive; we arbitrarily set this parameter to +4°C (keeping in mind that such a warming on a global scale would imply, in some regions, a warming greater than +6°C, that is to say tremendous local climatic shocks). With this specification, willingness to pay increases with the expected level of climate change. Moreover, the preservation of the current climate regime is treated as a superior good. This point can be quickly verified. Let WTP(θ) be the maximum amount of current income we are willing to pay to prevent a climate change of magnitude θ:

$$\ln(C).\left(\bar{\theta}-\theta\right)^{\beta}=\ln\left(C-WTP(\theta)\right).\left(\bar{\theta}\right)^{\beta} \qquad \text{leading to} \qquad WTP(\theta)=C-C^{\left(\frac{\bar{\theta}-\theta}{\bar{\theta}}\right)^{\beta}}$$

Hence, marginal willingness to pay is:

$$\frac{\partial WTP(\theta)}{\partial\theta}=\frac{\beta\ln C}{\bar{\theta}}\left(\frac{\bar{\theta}-\theta}{\bar{\theta}}\right)^{\beta-1}C^{\left(\frac{\bar{\theta}-\theta}{\bar{\theta}}\right)^{\beta}}>0$$

Therefore *WTP(θ)* is a growing function of temperature change *θ*.

Let *π(θ)* denote the ratio between *WTP(θ)* and income. We have:

$$\pi(\theta)=\frac{WTP(\theta)}{C}=1-C^{\left(\frac{\bar{\theta}-\theta}{\bar{\theta}}\right)^{\beta}-1} \qquad \text{leading to} \qquad \frac{\partial\pi(\theta)}{\partial C}=-\left(\left(\frac{\bar{\theta}-\theta}{\bar{\theta}}\right)^{\beta}-1\right)C^{\left(\frac{\bar{\theta}-\theta}{\bar{\theta}}\right)^{\beta}-2}>0$$

Thus, for the same climate change magnitude θ, π(θ) is an increasing function of income: climate protection is a superior good.

So far no opinion polls exist on the willingness to pay for climate stability; would they though, their results would be very sensitive to the political and/or media life cycles that determine the way information is conveyed to public opinion [19]. A more secure approach is to reveal the implicit utility function behind figures circulating about the *reasonable* maximum value for temperature change (for example +2°C in the Energy Modeling Forum ongoing round or for some NGOs). To do so, for each value of pure time preference (PTP), we can determine the elasticity of utility w. r. t. climate regime *(β)* that exactly balances the marginal welfare impacts of consumption and climate amenity value along the optimal abatement trajectories obtained for this target in the certainty case: practically, for this value of *β*, the marginal welfare impact of the consumption loss resulting from a tightening of the environmental objective from +2.05°C to +1.95°C is exactly compensated by the marginal welfare improvement due to lower temperatures. This procedure ensures consistency between claims for a given target and expectations on baseline emissions, abatement costs and climate sensitivity. For example, for a given abatement cost curve, a +2°C ceiling implies higher mitigation costs under high climate sensitivity. Sticking to this objective thus implies a higher WTP for climate protection than if one expects low climate sensitivity (see table 1).

Climate sensitivity	*2.5°C*	*3.5°C*	*4.5°C*
PTP = 1%.year^{-1}	1.4 10^{-4}	7.7 10^{-4}	13.8 10^{-4}
PTP = 3%.year^{-1}	2.7 10^{-4}	16.4 10^{-4}	34.4 10^{-4}

Table 1: Parameter β values in function of climate sensitivity and pure time preference

An important feature of the new program which maximizes U(.,.) without absolute constraint on the quality of the environment, is that an overshoot is now allowed in case of delayed action: this occurs if the cost of maintaining the temperature below the desired target is greater than the marginal WTP to avoid extra warming.

In *RESPONSE_P/c* all equations and model specifications remain identical to *RESPONSE_T/c* except the objective function which is re-specified as the maximization of an intertemporal utility function (1):

$$\underset{Ab_t}{Max} \sum_{t=1990}^{2300} N_t \ln\left(c \frac{\left(Y_t - f(Ab_t, Ab_{t-1}, t)\right)}{N_t} \right) \left(\overline{\theta} - \theta_t\right)^{\beta} e^{-\eta(t-1990)} \qquad (1)$$

with N_t the population level (source A1-m)

Y_t the gross world product (source A1-m)

c the propensity to consume (0.8)

β the elasticity of utility w. r. t. climate regime (see Table 1)

η the pure time preference (1 or 3%.year^{-1}, corresponding to 3 and 5%.year^{-1} discount rate in *RESPONSE_T/c*)

In a deterministic mode, it is first remarkable that there is no overshoot beyond a +2°C target for a 1% pure time preference, even in the most pessimistic value for climate sensitivity (results not shown here). A moderate overshoot (up to 0.15°C) during 50 years[3] is found with a pure time preference as high as 3% (Figure 3). Second, the model does not advocate lower abatement in the first periods: up to 2020 mitigation costs are twice as high as in a cost-efficiency framework. This paradox, noted by Hammitt [8], can be easily explained: in a cost-efficiency framework, agents give a high value to climate (the costate variable at a given point in time) only when the target is approached whereas in our PCCR approach, climate change is given a significant value by current generations. As time passes, future (and richer) generations give a higher value to it since it is a superior good.

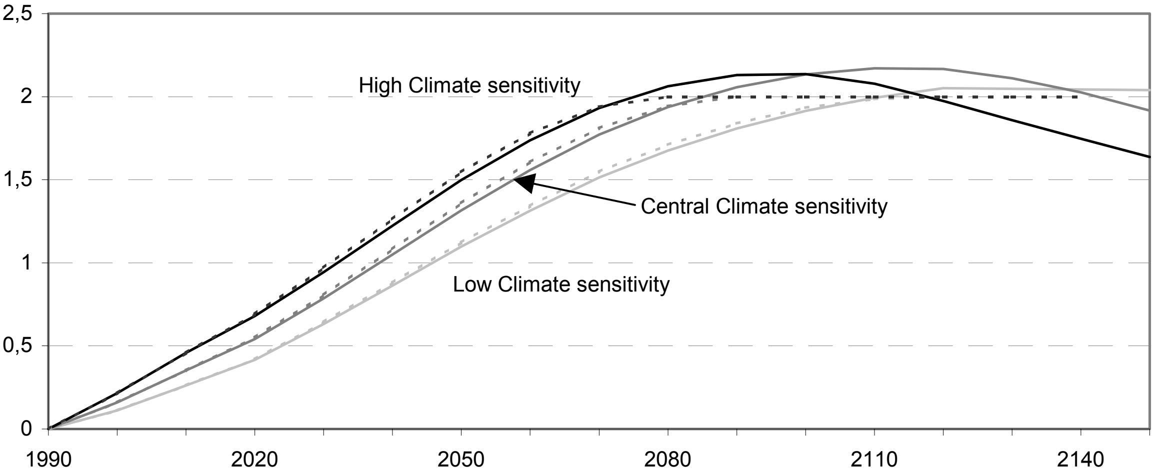

Figure 3 : Global mean temperature increase for 3 climate sensitivities: in a cost-benefit analysis with Pure Preference for Climate Current Regime based on a desired 2°C target (full curve) and in a cost-efficiency analysis with a 2°C target (dotted curve).

Let us now turn to a situation where, given the mandate of staying below a +2°C target for an expected +3.5°C value of climate sensitivity, the central planner calibrates the β coefficient accordingly ($\beta = \beta^C$ =0.00164) and considers the resulting utility function as expressing the real preferences of the population. But +3.5°C is only the mean of three possible values and as information arrives, climate sensitivity is set to its true value whereas the value of β is not revised.

This is captured by *RESPONSE_P/s* in which uncertainty on climate sensitivity specifications is similar to *RESPONSE_T/s*. *RESPONSE_P/s* parallels *RESPONSE_P/c* except its objective

[3] That figure should be considered cautiously because of the short-term calibration of the temperature model.

function which we specify such as the maximization of expected utility across the probability distribution of the three possible states of the world:

$$\underset{Ab_t^s}{Max}\sum_s p_s \sum_{t=1990}^{2300} N_t \ln\left(c\frac{\left(Y_t - f(Ab_t^s, Ab_{t-1}^s, t)\right)}{N_t}\right)\left(\overline{\theta} - \theta_t^s\right)^{\beta^C} e^{-\eta(t-1990)} \tag{1a}$$

Additional constraints (1b) are added to impose that, before the disclosure of information, decision variables be the same across all states of the world:

$$\forall t \le t_{info},\ \forall\left(s,s'\right)\in S,\ Ab_t^s = Ab_t^{s'} \tag{1b}$$

For a resolution of uncertainty as late as 2080, the optimal response leads to a +0.7°C overshoot if climate sensitivity is finally +4.5°C (dotted grey curve, Figure 4). This has to be compared to the modest overshoot in the certainty case (+0.1°C) (black thin curve, Figure 4). However, this overshoot does not mean an absence of action: the simulation shows a very significant deviation from the global mean temperature increase in the baseline scenario (bold black curve, Figure 4).

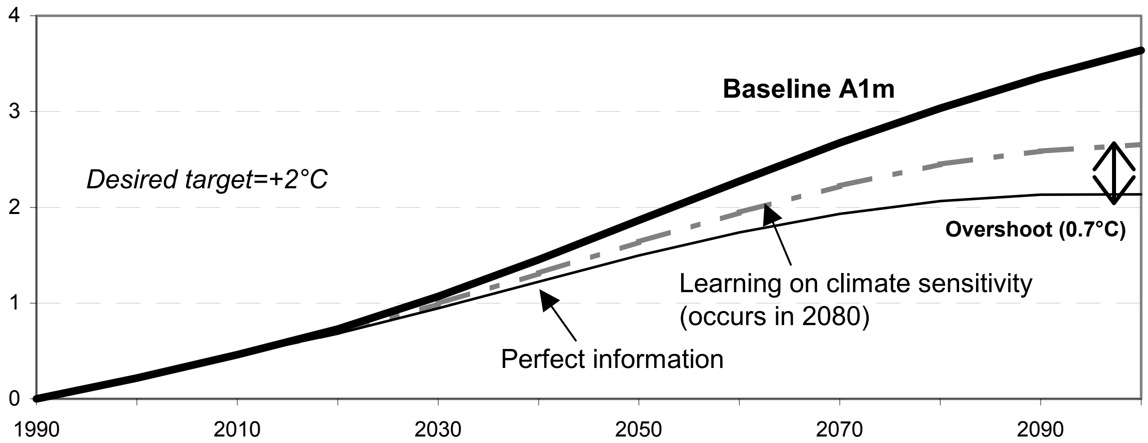

Figure 4 : Comparing the cost of misestimating belief on climate change damages and climate dynamics. In all cases, climate sensitivity has a high value. Global mean temperature increase for baseline case (bold black curve), for optimal strategy with perfect information (thin black curve) and for optimal strategy with learning on climate sensitivity (grey curve).

Consistently, under this pessimistic assumption regarding climate sensitivity, mitigation costs in the Kyoto commitment period are significantly lower in the learning case (β=16.4 10^{-4}) than in the perfect information case (β=34.4 10^{-4}): 0.02 % of GWP to be compared with 0.08 % of GWP. Sensitivity tests about the date of arrival of information on climate sensitivity show that mitigation costs around 2010 are remarkably constant and that the learning date has no dramatic influence on the magnitude of the overshoot, which varies from +0.6°C (early learning) to +0.7°C (late learning). These results suggest that the difference between β values dominates uncertainty regarding climate sensitivity.

The key question remains the real magnitude of WTP and its variations amongst regions depending on preferences and income level. At a regional level, such a PCCR analysis would enable to scrutinize compensation schemes between countries necessary to reach a consensus on a global temperature target. Some regions might indeed be willing to adopt a very low temperature ceiling corresponding to a global constraint too tight to be agreed upon at an international level. Would this global constraint be slackened, these regions would understandably demand for compensations.

5. Key issues with the strong form of cost-benefit analysis

Some authors are reluctant to resort to a cost benefit-analysis because, they claim, discounting cannot but underestimate the value of environmental damages and thus jeopardize future generations welfare. This seems the case in the few existing cost-benefit analyses (see the EMF review [20]), which univocally advocate a slow departure from current emission trends unless 'bad news' regarding climate damages appear.

Contrary to a PCCR approach, where environmental variations affect welfare in the first periods, climate impacts occur only several decades after mitigation efforts are undertaken and, once discounted, marginal benefits of those actions are easily outweighed by their costs. This is the reason why a zero coefficient for pure time preference (PTP) has been argued [21]. But this option faces serious problems. First, as shown by Koopmans [22], time consistent decision-making over infinite consumption plans requires a strictly positive PTP. In addition, introducing a zero or very low PTP in a growth model entails high savings and low consumption for the current (and poorest) generation. This is arguably not consistent with intergenerational equity.

This paper does not address the alternative proposals suggested in the literature to avoid the sacrifice of both current and future generations (e.g. [23]). Despite their interest, such proposals either raise serious dynamic consistency problems or do not change the response much for the early periods [24]. We rather concentrate on the interplay between conventional discounting and expectations regarding the shape of the damage function, future economic growth and future emissions. To this aim, we introduce a zero PCCR (β=0). Prior to discussing our results, which are mainly derived from numerical experiments, we present an analytical model to better understand the interplay between discount rate and the shape of the damage function, and demonstrate the importance on short term response of three parameters other than the shape of damage curve and discount rate: growth assumptions and emissions scenario, short term climate response and abatement cost functions.

5.1. Interplay between discount rate and the shape of the damage function

Let us start from a simple two-period decision model. At date t_1, a first decision is made to spend c_1 in abatement expenditures; in the same way, we spend c_2 in abatement expenditures at date t_2. Resulting damages, $D(c_1,c_2)$, befall at a posterior point in time. We define φ (the discount factor) as $\varphi=\frac{1}{1+\rho}$, ρ being the social discount rate.

The planner's optimal abatement schedule is solution of the following cost minimization problem, with n the number of years between t_1 and t_2 and m the distance between t_1 and the time at which damages occur ($m>n$):

$$\underset{c_1,c_2}{Min} \quad c_1+\varphi^n c_2+\varphi^m D(c_1,c_2)$$

The relationship between the slope of the damage function and the impact of the discount rate can be illustrated analytically by decomposing the damage function in two terms: an indicator of impacts $\theta(c_1,c_2)$ and a damage function *per se* $\Psi(\theta)$:

$$D(c_1,c_2)=\Psi[\theta(c_1,c_2)]$$

For illustrative purposes, let us assume that $\theta(.,.)$ has the following form, where α is strictly lower than unity to capture decreasing environmental return of abatement:

$$\theta(c_1,c_2) = a.c_1^{\alpha} + b.c_2^{\alpha}$$

The optimal abatement policy, (c^*_1, c^*_2) satisfies the following conditions:

$$\begin{cases} \alpha a\left(c_1^*\right)^{\alpha-1}\Psi_\theta\left(\theta^*\right) &= -\varphi^{-m} \\ \alpha b\left(c_2^*\right)^{\alpha-1}\Psi_\theta\left(\theta^*\right) &= -\varphi^{n-m} \end{cases} \quad \text{where} \quad \begin{cases} \Psi_\theta(.) &\equiv \dfrac{\partial\Psi}{\partial\theta} \\ \theta^* &= \theta\left(c_1^*,c_2^*\right) \end{cases}$$

Under the above assumptions, a rapid calculus shows that the variation of optimal first-period abatement when the discount rate varies from ρ to ρ' is as follows (where $'$ denotes the values of the variables for the alternative optimum):

$$\frac{c_1^{*'}}{c_1^*} = \left(\frac{1+\rho}{1+\rho'}\right)^{\frac{m}{1-\alpha}} \cdot \left(\frac{\psi_\theta\left(\theta^{*'}\right)}{\psi_\theta\left(\theta^*\right)}\right)^{\frac{1}{1-\alpha}}$$

If damages are linear in the environmental indicator (i.e. if $\psi_\theta(\theta)$ is constant) then the variation of first-period abatement becomes:

$$\frac{c_1^{*'}}{c_1^*} = \left(\frac{1+\rho}{1+\rho'}\right)^{\frac{m}{1-\alpha}}$$

If α=1/3 (which corresponds to quadratic marginal abatement costs) and m=100 years, a 1% increase of the discount rate implies a 76% decrease in first period marginal abatement costs.

But if marginal damages vary with the environmental indicator ($\Psi(\theta) = \theta^{-k}$), the variation of first period abatement becomes

$$\frac{c_1^{*'}}{c_1^*} = \left(\frac{1+\rho}{1+\rho'}\right)^{\frac{m}{1-\alpha}} \cdot \left(\frac{1+\xi\theta'^{\frac{-n\alpha}{1-\alpha}}}{1+\xi\theta^{\frac{-n\alpha}{1-\alpha}}}\right)^{\frac{k+1}{\alpha k+1}} \qquad \text{with } \xi = \left(\frac{b}{a}\right)^{\frac{1}{1-\alpha}}$$

If k=5 and b/a = 2 (technical change makes abatement twice less costly in the second period), the optimal first-period abatement diminishes only by 17% when the discount rate rises by 1%. Even if k=1 (quadratic damage function), first period abatement diminishes only by 45%. The impact of the discount rate on early decades abatement is thus strongly dependent on the interplay between the indicator of climate change and the damage function.

5.2. Importance of parameters other than the shape of damage curve

This critical role comes back again when comparing results from Dixit and Pyndick [25] on the one hand and Narain and Fisher [26] or Gjerde [27] on the other hand. Comparing the environmental irreversibility effect and the investment irreversibility effect, the former, using a real-option model, conclude to the dominance of the investment irreversibility effect in the case of a linear damage function, whereas the latters, including an avoidable climatic catastrophe in the analysis, find an opposite result. However, given the likely controversies about the shape of the damage function it would be misleading to focus on this sole parameter despite its critical significance. Three other key determinants of the timing of abatements are indeed of significance: a) the underlying growth scenario which dictates the level of the discount rate and the emissions baseline; b) the short term response of climate system to a given inflow of carbon and c) the abatement costs.

To demonstrate the importance of these determinants, we will introduce the following modifications in the DICE model ([12],[28]) while keeping its quadratic damages function of temperature rise[4]:

- we use the A1 SRES scenario as the baseline emissions (10.88 GtC and 12.64 GtC emissions in 2010 and 2020) instead of the DICE baseline which is very close to the B2 SRES scenario (8.78 GtC and 9.05 GtC emissions in 2010 and 2020 respectively),
- we modify the short term climate response *($\theta(c_1,c_2)$)*. DICE two-box climate model provides a fair description of long-term climate change but underestimates short term atmospheric temperature rise because of the specification of upper and lower compartments (atmosphere and superficial ocean, deep ocean). This is not the case with the climate model presented in Appendix A: though similar to the one in DICE, it has been calibrated so as to describe more precisely short-term climate change.
- we retain a marginal abatement cost curve as exposed in Appendix A. The specification is quadratic and accounts for socio-economic inertia. It leads to an equivalent burden for 2010 (0,35% of GWP as compared to 0,36% of GWP following DICE specifications) but with a moderately lower price of carbon: 60$/tC instead of 75$/tC.

Figure 5 demonstrates that changing the specification $\theta(c_1,c_2)$ or choosing an alternative emissions baseline raises abatement rates in 2015 from 5.6% to 7.2% (resp. 5.6% to 8.6%). When both effects are combined, the abatement rate variation is increased by 50% (from 5.6% to 8.6%). It is more than doubled (from 5.6% to 12.5%) if abatement costs are 20% lower.

These results do not pretend to be conclusive about the validity of the Kyoto Protocol. They simply underline that, even without singularity in damage functions, the optimal level of departure from current trends is sensitive to the description of short term climate response and emissions trends, in addition to the value of the discount rate.

[4]We used DICE99 version available at http://www.econ.yale.edu/%7Enordhaus/homepage/dice_section_IV.html Damage function is polynomial of degree 2. Both coefficients are positive so they do not allow for global benefits of climate change for low temperature change. Benchmark corresponds to a 1.5% GWP loss for a 2.5°C global mean temperature rise. Furthermore, the argument of DICE-99 damages function is global mean temperature rise since 1900. To keep results comparable, we reformulated DICE including the following modification: the argument of the damages function becomes global mean temperature rise relative to the first period of the model (1995).

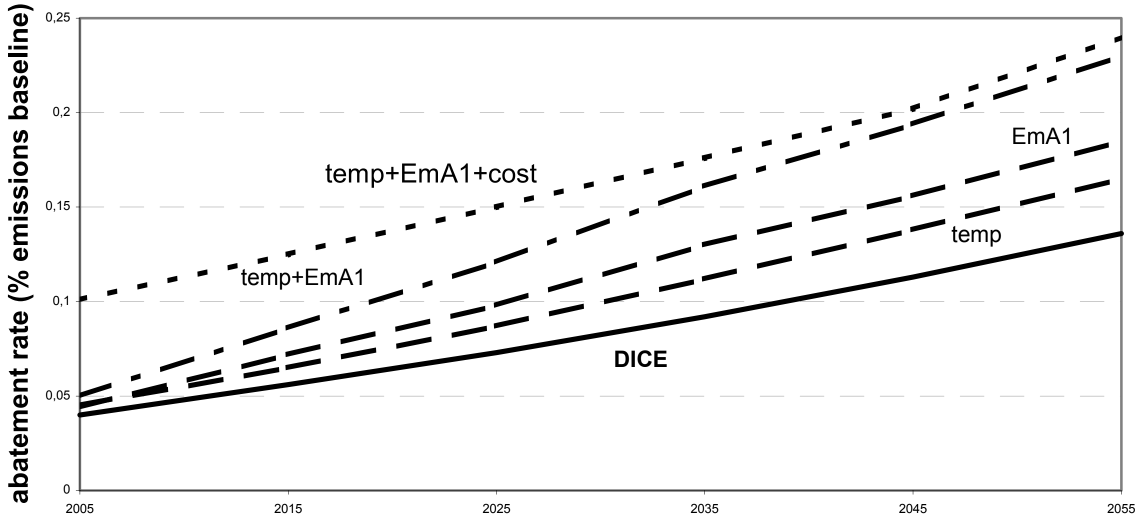

Figure 5: Abatement rate for DICE and for DICE including the modified temperature model ("temp"), a different baseline ("EmA1"), both former modifications ("temp+EmA1") and finally same than before with the new cost curve ("temp+EmA1+cost").

5.3. Interplay between the shape of damage curve and climate sensitivity

Let us now turn to the numerical analysis of the linkages between the timing of GHGs abatement, the value of the discount rate and that of the time derivative of damages which are critical for early decades actions (see 5.1). This raises the question of singularities triggered by the interplay between climate change $\theta(.)$ and the responses of environmental and socio-economic systems $\psi(.)$.

Recently, concerns about such singularities have been evoked beyond environmentalist quarters[5]: "[My] biggest fear is that international policy is being made based on smooth climate change" (G. Yohe). It is hardly disputable that potential sources of abrupt impacts exist along the chain from global warming to changes in local ecosystems. Large scale catastrophic events are the most obvious examples: slow-down of the thermohaline circulation in the North Atlantic, transformation of monsoons patterns or of El Niño cycles. Local climate surprises may also be triggered by smooth evolutions as soon as a threshold is exceeded: for example coral reefs could experience severe bleaching episodes due to a warming of sea surface temperature.

But one major layer of uncertainty lies in the very translation from impacts to losses in social welfare. On the one hand, archaeologists [30] establish coincidences between sudden climate shifts and deep societal mutations; on the other hand, it can be argued that technologically advanced societies are far more resilient. But this response in turn shows that damages depend strongly on the mobilization of adaptation capacities, among which compensations between 'winners' and 'losers'. For example, variation of crops productivity, triggered by changes in temperature, CO_2 concentration, rainfall regime or soil degradation, will also depend upon the capacity to invest in water management systems in affected regions and/or to cover the basic needs of their populations through an accessible world market. In the same way, higher frequency of extreme events may aggravate the vulnerability of countries with fragile socio-

[5] The Boston Globe (December, 12 2002) on the occasion of the publication announcement of the National Academies report "Abrupt climate change: inevitable surprises" [29].

economic systems; for example the political disorganization in Guatemala cannot be fully isolated from the catastrophes that have been affecting this country in the past several years.

5.3.1. Smooth vs threshold function: levels and rates of climate damages

A review of the main shortcomings of widely-used impact functions can be found in [2] (chap. XIX). In the perspective of analyzing short-term response to climate change, the main drawbacks of these functions can be exemplified with the DICE-94 damage function [28]. This function is close to $a_1(\theta)^{a_2}$, where θ stands for global mean temperature rise since 1900 (benchmark estimate is a 1.33 % GWP loss for a +3°C global mean temperature increase; for a_2=2, we obtain a_1=1.33/9). Base value of a_2=2 has greatly influenced previous studies. But such a function has three intrinsic drawbacks:

- climate surprises leading to high GWP losses can only be represented by adopting unrealistically high global mean temperature rise values. As an example, referring to DICE-94 damage function, the global mean temperature rise corresponding to a 10% GWP loss (which is higher than the economic shock of WWI) amounts to more than +8°C.
- if a higher exponent is selected so as to lower the global mean temperature rise corresponding to this 10% GWP loss (for a_2=4, this rise is +5°C), this leads to the paradoxical consequence that the larger the long-term damages, the smaller the short term ones (because of an increased convexity).
- lastly, multiplying the scale parameter of the damage function (a_1) to get more realistic damages on the short term (without altering the convexity of the function) also quickly leads to unrealistic high damages on the longer term.

One technical option allowing to represent the episodes of very significant damages without assuming unrealistic temperature increases is the use of sigmoid-like functional forms [31]. To carry out simulations comparable with our previous cost-efficiency analysis, we set the middle of the threshold to +2°C (with a transition range from 1.7°C to 2.3°C). The maximum damage plateaus at a 4% GWP loss.

To clarify the interplay of assumptions regarding the shape of damage functions with climate sensitivity, we compare in this section how, given the uncertainty on climate sensitivity, the timing of mitigation policies is affected by the specification of damage functions (threshold vs quadratic). In the next section, we perform a set of complementary simulations where climate sensitivity is known (set to its central value) whereas damages are subject to beliefs on the occurrence of singular events.

5.3.2 Threshold vs quadratic function under climate dynamics uncertainty: **RESPONSE_D**

Let us first note that, under assumption of singularities in the damage curve, climate sensitivity determines the period at which the time derivative of damages becomes higher than the discount rate. This is demonstrated in Figures 6 and 7: the 4% GWP loss is reached in 2050 or 2100, depending upon assumptions on climate sensitivity.

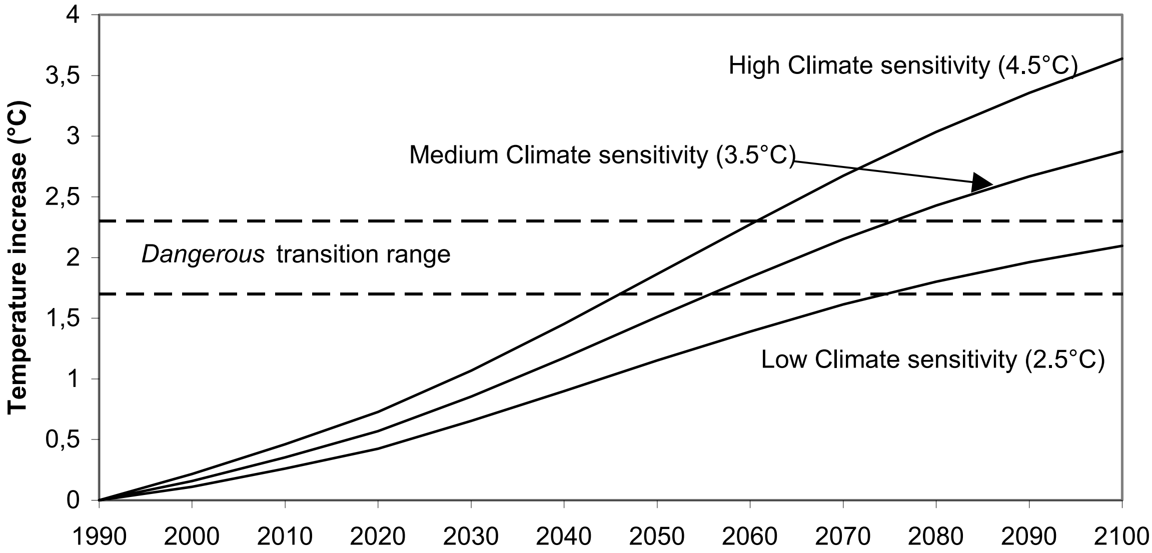

Figure 6: Global mean temperature rise with respect to 1990, with A1 emission baseline and three values for climate sensitivity.

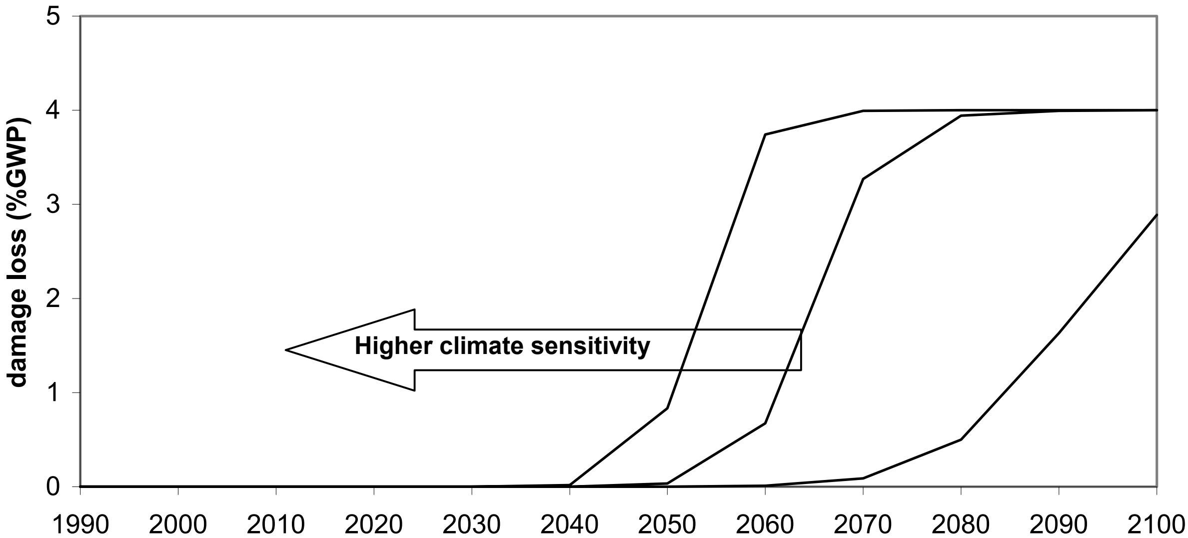

Figure 7: Depending on the value of climate sensitivity, in the case of singularities around a +2°C warming threshold, abrupt shifts (in the baseline case) occur sooner as climate sensitivity is higher.

Let us now consider three possible states of the world *(s)* in which climate sensitivity may be {2.5°C;3.5°C;4.5°C} with the corresponding *ex ante* subjective probabilities *(p_s)* = {1/6;2/3;1/6}. The resolution of the uncertainty may occur at different points in time during the 21st century (t_{info}). Damage functional forms are assumed to be known in each simulation and are either quadratic or sigmoid. They have been calibrated so that their total expected damages follow comparable trajectories in the reference case up to 2100. However, beyond 2100, quadratic damages are far higher than threshold ones; this has significant consequences on abatement pathways.

To analyze the impacts of these mechanisms on the optimal pathway, we performed numerical experiments based on the *RESPONSE_D/s* variant of our generic model, in which the objective function (1a) is the maximization of the expected intertemporal (logarithmic) utility of income, Y, minus abatement costs, *f(.)* and resulting damages, $\Psi(.)$:

$$\underset{Ab_t^s}{Max} \sum_s p_s \sum_{t=1990}^{2300} N_t \ln\left(\frac{\left(Y_t - f(Ab_t^s, Ab_{t-1}^s, t) - \Psi(\theta_t^s, t)\right)}{N_t}\right) e^{-\eta(t-1990)} \qquad (1a)$$

Damages functions are the following:

quadratic damages function

$$\Psi\left(\theta_t^s, t\right) = a\left(\theta_t^s\right)^2 Y_t$$

threshold damages function

$$\Psi\left(\theta_t^s, t\right) = \left(\frac{d}{1+\left(\frac{2-e}{e}\right)^{\left(\frac{K+Z-2\theta_t^s}{K-Z}\right)}} + b\theta_t^s\right) Y_t$$

with a=0.6%GWP, d=4% of GWP, e=0.01, Z=1.7°C, K=2.3°C, b=0.5 %GWP.

As in earlier versions, learning process is represented by the following constraint (1b):

$$\forall t \le t_{\inf o},\ \forall\left(s, s'\right) \in S,\ Ab_t^s = Ab_t^{s'} \qquad (1b)$$

Figure 8 shows the optimal emission paths for quadratic (dashed grey curves) and threshold damage functions (grey curves) when learning on climate sensitivity occurs in 2020 or 2040. No direct policy conclusion can be derived from the comparison between both emissions paths[6], since the ultimate damages levels for each shape are not equal. This explains why the abatement pathways are comparable in the early periods. The main information from this experiment is that, if information on climate sensitivity arrives later than 2030, threshold functions lead to higher abatement rates and that the value of information on climate sensitivity (Figure 9) increases very significantly. This is due to the fact that one gets close to the threshold, a mechanism which does not appear with quadratic functions. This confirms Peck and Teisberg findings [32] that the value of information gets higher the more non-linear damages are. In policy terms, this confirms the existence of a window of opportunity, already found in the cost-efficiency analysis with temperature ceiling and in the PCCR approach.

[6] In particular the fact that optimal emissions paths are similar until 2030 should be considered as a calibration artefact.

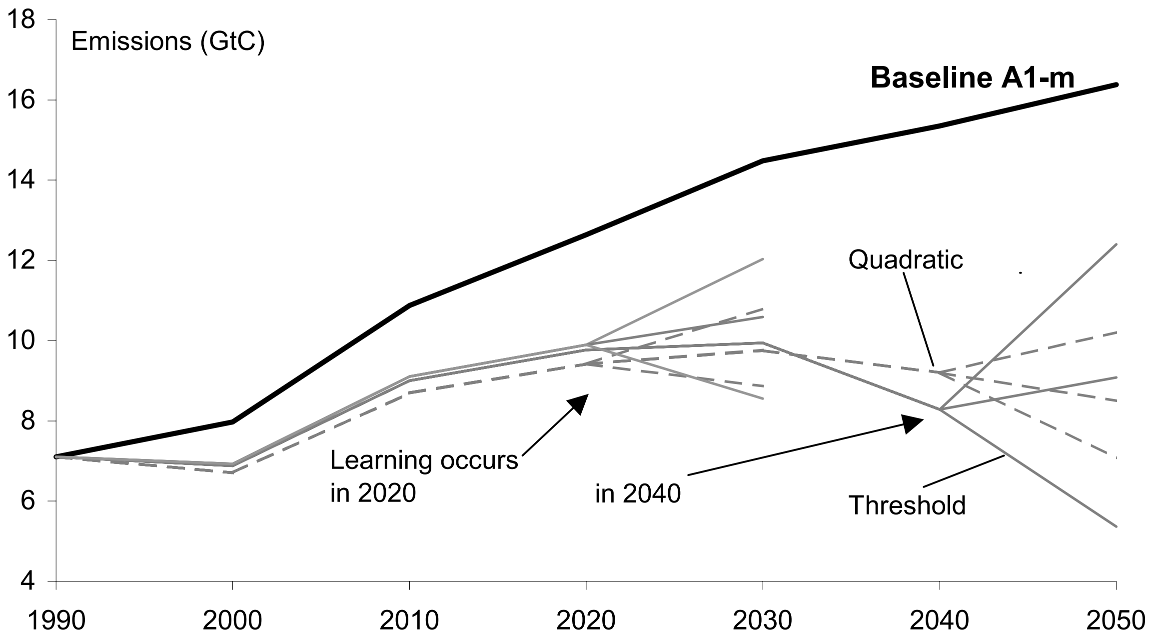

Figure 8: Emissions path for quadratic(dashed grey curves) and threshold (full grey curves) damage functions and learning on climate sensitivity in 2020 or 2040.

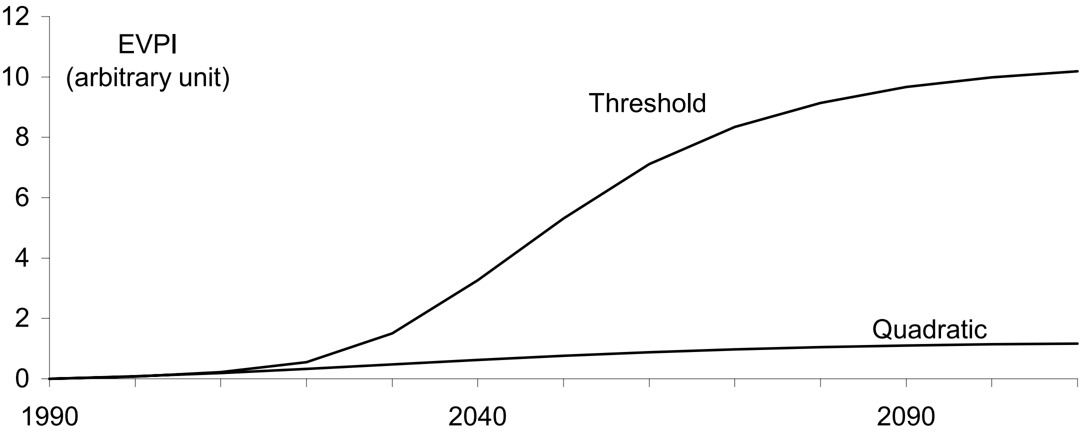

Figure 9: Expected Value of Perfect Information on climate sensitivity for quadratic and threshold damage functions.

5.3.3 Uncertainty regarding damage function when climate dynamics is known

To analyze the specific importance of uncertainty on the shape of damage function, we calibrated both specifications on the same arbitrary benchmark value: 1% GWP loss for a 2°C temperature increase. Climate sensitivity is assumed to be known and set to its central value (3.5°C). Moreover, expected damages exhibit similar temporal trends at least during the first half of the current century.

This comes to respecifying *RESPONSE_D'*/s objective function in the following manner. *Ex ante* subjective probabilities (p_s) are assigned to two states of the world (s): either damages functions are quadratic (Q) or they exhibit threshold (T). To reflect the diversity of beliefs, we have tested four sets of values for p_S: $\{p_Q=1,\ p_T=0\};\{p_Q=0.95,\ p_T=0.05\};\{p_Q=0.5,\ p_T=0.5\};\{p_Q=1,\ p_T=0\}$. Objective function (1a) is the maximization, for each set of subjective probabilities, of expected intertemporal (logarithmic) utility of income, Y, minus abatement costs, $f(.)$ and resulting damages, $\Psi(.)$:

$$\underset{Ab_t^s}{Max}\sum_s p_s \sum_{t=1990}^{2300} N_t \ln\left(\frac{\left(Y_t - f(Ab_t^s, Ab_{t-1}^s, t) - \Psi_s(\theta_t^s, t)\right)}{N_t}\right) e^{-\eta(t-1990)} \qquad (1a)$$

with

$$\Psi_s(\theta,t) = \begin{cases} a\left(\theta_t^s\right)^2 Y & s = Quadratic \\ \left(\dfrac{d}{1+\left(\dfrac{2-e}{e}\right)^{\left(\frac{K+Z-2\theta}{K-Z}\right)}}\right) Y_t & s = Threshold \end{cases}$$

with a=0.25% of GWP, d=3% of GWP, e=0.01, Z=1.7°C, K=2.3°C, b=0.5 %GWP.

As earlier, learning process is represented by the following constraint (1b):

$$\forall t \le t_{\inf o},\ \forall (s,s') \in S,\ Ab_t^s = Ab_t^{s'} \qquad (1b)$$

Because quadratic functions refer to ultimate damages far higher than threshold functions, abatement rates are similar in the early decades. This is why results in Figure 10 show the same limitations than in Figure 9. However despite this artefact, abatement pathways diverge significantly if information is disclosed after 2030. After this date, the optimal pathways are critically dependent on the subjective probability sets: it is remarkable however that a 5% subjective probability only for the threshold function (upper dotted line) leads to a significant departure from the quadratic case while a 50/50 distribution of probabilities leads to emissions pathway very close to the optimal pathway in case of early certainty about the existence of the threshold. Here again, the worst case hypothesis dominates the result.

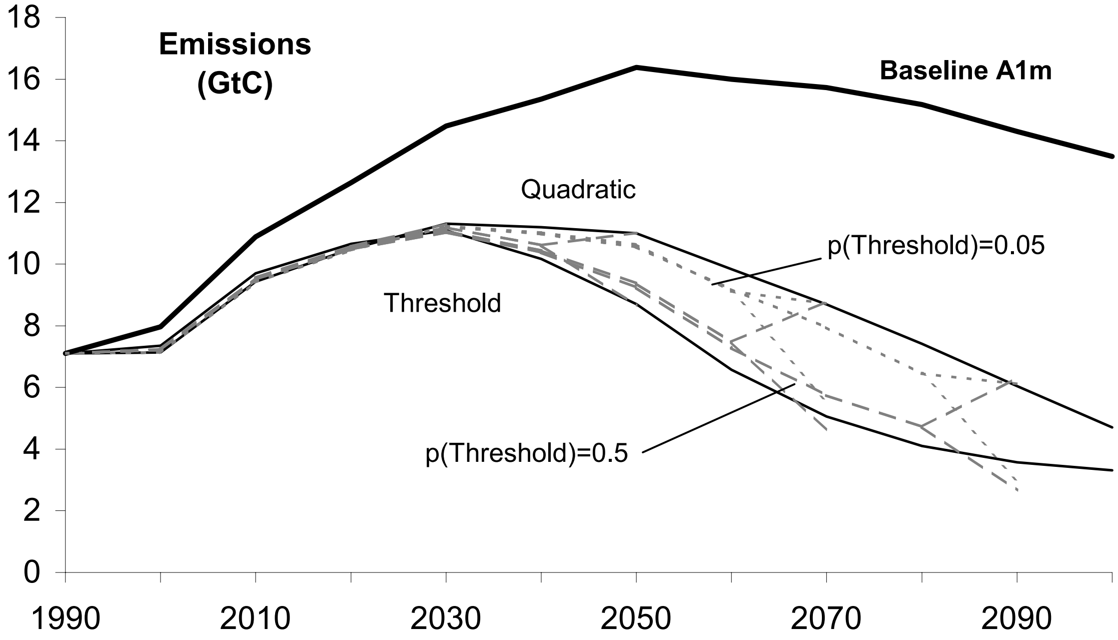

Figure 10: Emissions paths for different subjective probabilities of the threshold function with learning. Threshold function probability : 0% for the upper thin black line; 5% for the dotted grey line, 50% for the dashed grey line; 100% for the lower thin black line.
Learning occurs in 2040, 2060 and 2080

6. Conclusions

In this paper, we have compared optimal climate policy in the short run under three different decision-making frameworks: cost-effectiveness with temperature ceiling objectives, cost-benefit analysis with pure preference for current climate regime and full cost-benefit approach with monetized evaluations of impacts. Five key lessons on short term decision emerge from this analysis.

(a) Given the cascade of uncertainty from emissions to damages, the difference between various decision-making frameworks appears to matter less than the difference between stochastic and non stochastic approach.

(b) In a stochastic approach, it is not necessary to assume ultimate catastrophic impacts to conclude to the optimality of early GHGs abatements. Singularities in the damage curves are sufficient to draw such a conclusion mainly because they increase the role of the uncertainty on climate sensitivity. In a stochastic framework, with uncertainty about the shape of the damage curve, the choice of the optimal strategy is dominated by the likelihood of occurrence of function with singularities.

(c) In addition to the shape of damage curves, the optimal timing of emissions abatement is very sensitive to the way the carbon cycle, the climate sensitivity and baseline emissions over the first decades are calibrated, and to the extent to which their intrinsic uncertainty is considered.

(d) A window of opportunity exists in all decision-making frameworks, cost-benefit analysis with smooth damage curves excepted. The value of information is low in the first periods but increases drastically after 2020 to 2040. This time-horizon has to be compared with the fifty years necessary to change energy systems, and to the fact that, according to the climate models, clear signals may not emerge from the noise of climate variability before 2050.

(e) The introduction of a pure preference for current climate allows for an overshoot of desired temperature (or concentration) targets without lowering the first period effort because it counterbalances the influence of discounting, all the more so as the environment is treated as a superior good.

The core difficulties remain: a) the revelation of the pure preference for current climate regime (including its volatility due to the media life cycles), b) the evaluation of the interplay between the various influences of climate change on the economy. Among these interplays we will insist, as an invitation to further thoughts, on the role of the inertia and of the geographical distribution of damages. One major source of singularity in damage curves comes indeed from the joint effect of uncertainty and the inertia of human systems: a two percent of GDP loss may either represent a benign shock when spread over a century or a havoc when concentrated on five years (this is the cost of WW1 for France). Another related source of singularity is the propagation effect (climate refugees for example), in case of un-compensated shocks at a local level.

Coping with these difficulties will confront the methodological difficulties of incorporating intrinsically controversial information at various spatial scales, including information derived from 'grass-root' case studies, into an integrated modeling framework. The increase of the size of the models to be mobilized will make all the more necessary the development of compact models of the sort used in this paper. Both mathematically controllable and flexible enough, they are an appropriate communication tool between scientific disciplines and between science and stakeholders in a process of public decision-making under scientific controversy.

Appendix A

A.1. Baseline growth scenario and exogenous related data (income and population)

All experiments are based on the SRES A1m scenario which has been computed by NIES (National Institute for Environmental Studies, Japan) with the AIM model (Asian Pacific Integrated Model) [33]. We choose the A1m scenario because it corresponds to rather optimistic beliefs about the future. A1m is indeed the picture of a prosperous and generous world where economic growth is high with a considerable catch-up of developing countries, continuous structural change and rapid diffusion of more efficient technologies yield to decreasing GHGs emissions as soon as 2050. A1m is thus consistent with beliefs such as "*it is better to invest in R&D in the energy sector and/or research in climate change-related fields than to deep-cut fossil fuel emissions at once while alternative technologies are expensive and climate change consequences might prove ultimately benign*" or "*abatement opportunity cost is lower than that of fostering development in potential vulnerable regions*". It is therefore relevant to examine how statements like "*one should delay GHGs emissions reduction efforts*" are to be revised when using a proper precautionary approach.

A.2. Specification of abatement cost function

We use the following abatement cost function:

$$f(Ab_t, Ab_{t-1}, t) = \frac{1}{3} BK.PT_t.\gamma\left(Ab_t, Ab_{t-1}\right).em_t.\left(Ab_t\right)^3$$

with: $f(Ab_t,Ab_{t-1},t)$ total cost of mitigation measures at time t (trillion US$)
- BK initial marginal cost of backstop technology (thousand US$.tC^{-1})
- PT_t technical change factor
- $\gamma(Ab_t,Ab_{t-1})$ socio-economic inertia factor
- em_t baseline CO_2 emissions at time t (GtC)
- Ab_t abatement rate at time t (% of baseline emissions)

Under these specifications, marginal costs of abatament are convex (quadratic). This is consistent with assumptions by experts and the results of technico-economic models. Note that f(.) does not allow for so-called no-regret potential.

BK stands for the initial marginal cost of backstop technology, ie the carbon free-technology which would enable to completely reduce GHGs emissions were it to be substituted to current existing energy systems. Its value depends on a set of assumptions regarding its nature (windpower, nuclear, …), its development date, its penetration rate and technical change. Given our own assumptions on technical change, we retain an initial 1,100US$.tC^{-1} cost.

PT_t captures the influence of autonomous technical change on abatement costs. It translates the decrease of the costs of carbon-free technology over time, but the improvement of energy intensity which is already taken into account in the baseline. We assume that the costs of abatement technologies decrease at a constant 1% per year rate but we assume costs cannot decrease beyond 25% of their initial values. PT_t thus take the form below (which leads to an ultimate cost of 275 US$.tC^{-1})

$$PT_t = 0.25 + 0.75 e^{-0.01\delta t}$$

where: δ is the time step of the model (10 years)

$\gamma(Ab_t,Ab_{t-1})$ captures the influence of socio-economic inertia as a cost-multiplier (transition costs between a more and a less carbon-intensive economic structure). $\gamma(.)$ is a multiplicative index. It is equal to 1 (no additional costs) if abatement increases at a rate lower than a given threshold τ between two consecutive periods. But it increases linearly with the speed of variation of abatement rate when this rate is higher than τ, i.e. the annual turnover of productive capital below which mitigation policies do not lead to premature retirement of productive units. Here τ is set to 5% per year (average capital stocks turnover of 20 years).

$$\gamma\left(Ab_t, Ab_{t-1}\right) = \begin{cases} 1 & \text{if } \dfrac{Ab_t - Ab_{t-1}}{\delta\tau} \le 1 \\ \dfrac{Ab_t - Ab_{t-1}}{\delta\tau} & \text{otherwise} \end{cases}$$

A.3. Three-reservoir linear carbon-cycle model

We use the C-Cycle of Nordhaus [12], a linear three-reservoir model (atmosphere, biosphere + surface ocean and deep ocean). Each reservoir is assumed to be homogenous (well-mixed in the short run) and is characterised by a residence time inside the box and corresponding mixing rates with the two other reservoirs (longer timescales). Carbon flows between reservoirs depend on constant transfert coefficients. GHGs emissions (CO_2 solely) accumulate in the atmosphere and they are slowly removed by biospheric and oceanic sinks.

The dynamics of carbon flows is given by is given by:

$$\begin{pmatrix} A_{t+1} \\ B_{t+1} \\ O_{t+1} \end{pmatrix} = C_{trans} \cdot \begin{pmatrix} A_t \\ B_t \\ O_t \end{pmatrix} + \delta\,(1 - Ab_t) em_t . u$$

with
- A_t carbon contents of atmosphere at time t (GtC)
- B_t carbon contents of upper ocean and biosphere at time t (GtC)
- O_t carbon contents of deep ocean at time t (GtC)
- C_{trans} net transfert coefficients matrix
- u column vector (1,0,0)

As such, the model has a built-in ten-year lag between CO_2 emissions and CO_2 accumulation in the atmosphere, which reflects the inertia in C-cycle dynamics. Nordhaus calibration on existing carbon-cycle models gives the following results (for a decadal time step):

$$C_{trans} = \begin{pmatrix} 0.66616 & 0.27607 & 0 \\ 0.33384 & 0.60897 & 0.00422 \\ 0 & 0.11496 & 0.99578 \end{pmatrix} \qquad \text{initial conditions (GtC):}\; C_{1990} = \begin{pmatrix} 758 \\ 793 \\ 19\,230 \end{pmatrix}$$

The main criticism which may be addressed to this C-cycle model is that the transfer coefficients are constant. In particular, they do not depend on the carbon content of the reservoir (*e.g.* deforestation hindering biospheric sinks) nor are they influenced by ongoing climatic change (*eg* positive feedbacks between climate change and carbon cycle).

A.4. The reduced-form climate model[7]

This model is very close to Schneider and Thompson's two-box model [34]. A set of two equations is used to describe global mean temperature variation (eq. 2) since pre-industrial times in response to additional human-induced forcing (eq. 1). More precisely, the model describes the modification of the thermal equilibrium between atmosphere and surface ocean in response to anthropogenic greenhouse effect. Calibration was carried out with H. Le Treut (IPSL) from data kindly provided by P. Friedlingstein (IPSL).

All specifications correspond to decadal values, which is the time step of the model.

Radiative forcing Equation:

$$F(t) = F_{2X} \frac{\log\left(\dfrac{M_t}{M_{PI}}\right)}{\log 2} \qquad (1)$$

with
- M_t: CO_2 atmospheric concentration at time t (ppm)
- F(t): radiative forcing at time t ($W.m^{-2}$)
- M_{PI}: CO_2 atmospheric concentration at pre-industrial times, set at 280 ppm.
- F_{2X}: instantaneous radiative forcing for 2x M_{PI}, set at 3.71 $W.m^{-2}$.

---

[7] A more precise description of the model and calibration process may be found in [17].

Temperature increase Equation:

$$\begin{cases}\begin{bmatrix}\theta_{At}(t+1)\\ \theta_{Oc}(t+1)\end{bmatrix}=\begin{bmatrix}1-\sigma_1(\lambda+\sigma_2) & \sigma_1\sigma_2\\ \sigma_3 & 1-\sigma_3\end{bmatrix}\begin{bmatrix}\theta_{At}(t+1)\\ \theta_{Oc}(t+1)\end{bmatrix}+\sigma_1\begin{bmatrix}F(t)\\ 0\end{bmatrix}\end{cases} \quad (2)$$

with $\theta_{At}(t)$: global mean atmospheric temperature rise wrt pre-industrial times (°C)
$\theta_{Oc}(t)$: global mean oceanic temperature rise wrt pre-industrial times (°C)

and λ: climate response parameter ($C^{-1}.W.m^{-2}$)
σ_1: transfert coefficient (set at 0.479 $C.W^{-1}.m^2$)
σ_2: transfert coefficient (set at 0.109 $C^{-1}.W.m^{-2}$)
σ_3: transfert coefficient (set at 0.131)

Climate sensitivity (T_{2x}) is given by $T_{2x}= F_{2X} / \lambda$. We assume that uncertainty is mainly due to uncertainty on (atmospheric) climate feedbacks process (represented by λ) rather than uncertainty on F_{2X}. A high climate response parameter will lead to a low climate sensitivity. We explore three values for climate sensitivity and λ is set accordingly to F_{2x}/T_{2X} see following table:

State of the World	*LOW*	*CENTRAL*	*HIGH*
Climate sensitivity (T_{2x})	2.5°C	3.5°C	4.5°C
Ex ante subjective probability (p_s)	1/6	2/3	1/6
λ	1,48	1,06	0,82

A.5. Numerical resolution

To avoid boundary effects, we did not specify terminal conditions in 2100 but set the time horizon of the model at 2300. All the models have been run under the GAMS-MINOS non-linear solver. The model codes are available from the authors on request.

Acknowledgements

The authors wish to acknowledge financial support from the French Ministry of Ecology and Sustainable Development and French Interministerial Mission on Climate Change through the GICC Research Program (No.10/99). We would also like to thank Vincent Gitz, Frédéric Ghersi and an anonymous reviewer for helpful remarks and comments. The remaining errors are entirely the authors'.

Disclaimer

The findings, interpretations and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the view of the World Bank, its Executive Directors, or the countries they represent.

References

1. *United Nations Framework Convention on Climate Change*. 1992.
2. McCarthy, J. J., et al., eds. *Climate Change 2001: Impacts, adaptation and vulnerability. Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change*. 2001, Cambridge University Press: Cambridge (UK & US).
3. Bruce, J.P., H. Lee, and E.F. Haites, eds. *Climate change 1995: Economic and social dimensions of climate change. Contribution of Working Group III to the Second Assessment Report of the Intergovernmental Panel on Climate Change*. 1996, Cambridge University Press: Cambridge (UK&US).
4. Metz, B., et al., eds. *Climate Change 2001: Mitigation. Contribution of Working Group III to the Third Assessment Report of the Intergovernmental Panel on Climate Change*. 2001, Cambridge University Press: Cambridge (UK & US).
5. Lave, L.B., *Formulating greenhouse policies in a sea of uncertainties.* Energy Journal, 1992. **12**(1): p. 9-21.
6. Costanza, R., et al., *The value of the world's ecosystem services and natural capital.* Nature, 1997. **387**: p. 253-260.
7. Toman, M.A., *Why not to calculate the value of the world's ecosystem services and natural capital.* Ecological Economics, 1998. **25**(1): p. 57-60.
8. Hammitt, J.K., *Evaluation endpoints and climate policy: atmospheric stabilisation, benefit-cost analysis and near-term green-house gas emissions.* Climatic Change, 1999. **41**: p. 447-468.
9. Ha Duong, M., M. Grubb, and J.C. Hourcade, *Influence of socioeconomic inertia and uncertainty on optimal CO_2-emission abatement.* Nature, 1997. **390**: p. 270-274.
10. Wigley, T.M.L., R. Richels, and J.A. Edmonds, *Economic and environmental choices in the stabilization of atmospheric CO_2 concentrations.* Nature, 1996. **379**: p. 240-243.
11. Houghton, J. T., et al., eds. *Climate change 2001: the scientific basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change*. 2001, Cambridge University Press: Cambridge (UK&US).
12. Nordhaus, W. and R. Boyer, *Warming the world: Economics models of Climate Change*. 1999, Cambridge (MA, USA): MIT Press.
13. Parry, M., et al., *Millions at Risk: defining critical climate change threats and targets.* Global Environmental Change, 2001. **11**: p. 181-183.
14. Simonett, O., *Potential impacts of global warming: cases studies on climatic change*. 1989, GRID-Geneva: Geneva (Switzerland).
15. EU, *Communication on Community strategy on Climate Change: Council conclusions*. 1996: Brussels.
16. Manne, A.S. and R. Richels, *Buying Greenhouse Insurance: The Economic Cost of CO_2 Emissions limits*. 1992, Cambridge (MA, USA): MIT Press.
17. Ambrosi, Ph., J.C. Hourcade, and H. Le Treut, *Incertitudes sur la sensibilité du climat: valeur de l'information et politique climatique optimale*, in *Modélisation intégrée, évaluation des risques climatiques et des politiques de précaution*, J.C. Hourcade and H. Le Treut, Editors. 2002: Progamme GICC (Mate/MIES/Ademe), Rapport final.
18. Hourcade, J.C. and T. Chapuis, *No-regret potentials and technical innovation.* Energy Policy, 1995. **23**(4/5): p. 433-445.
19. Scimeni, G., *Environmental strategies and anticipatory strategies*, in *Preventive environemental policy*, C.E. Simonis, Editor. 1987, Campus: NY (USA).
20. Manne, A.S., *Hedging strategies for global carbon dioxide abatement: a summary of poll results, EMF-14 Sub group - Analysis for decision under uncertainty*. 1995, Stanford University: Stanford (CA).

21. Cline, W. R., *La lutte contre l'effet de serre.* Finance et développement, 1996. **30**(1): p. 4-6.
22. Koopmans, T.C., *Stationary ordinal utility and impatience.* Econometrica, 1960. **28**(2): p. 287-309.
23. Chichilnisky, G., *An axiomatic approach to sustainable development.* Social choice and welfare, 1996. **13**(2): p. 231-257.
24. Lecocq, F. and J.C. Hourcade, *Incertitude, irréversibilités et actualisation dans les calculs économiques sur l'effet de serre*, in *Les enjeux économiques de l'effet de serre*, R. Guesnerie, Editor. 2003, La Documentation Française: Paris. p. 177-199.
25. Dixit, A.K. and R.S. Pyndick, *The timing of environmental policy*. 1994, Princeton (NJ, USA): Princeton University Press.
26. Narain, U. and A.C. Fisher, *Global warming, endogenous risk and irreversibility*. 2002, Department of agricultural and resource economics-UC Berkeley (CA, USA).
27. Gjerde, J., S. Grepperud, and S. Kverndokk, *Optimal climate policy under the possibility of a catastrophe.* Resources and Energy Economics, 1999. **21**: p. 289-317.
28. Nordhaus, W., *Managing the Global Commons: the Economics of Climate Change*. 1994, Cambridge(MA, USA): MIT Press.
29. Alley, R., ed. *Abrupt climate change: inevitable surprises*. 2002, National Academy Press: Washington DC.
30. Weiss, H. and R.S. Bradley, *What drives societal collapse?* Science, 2001: p. 609-610.
31. Dumas, P. and M. Ha Duong. *Non-linearities and uncertain climate impacts*. in *Energy Modeling Forum (EMF)*. 2001. Laxenburg(Austria).
32. Peck, S. and T. Teisberg. *The importance of nonlinearities in global warming damage costs*. in *Assessing surprises and nonlinearities in greenhouse warming*. 1993. Washington DC: RFF.
33. Nakicenovic, N., ed. *Special Report on Emissions Scenarios: a special report of Working Group III of the Intergovernmental Panel on Climate change*. 2000, Cambridge University Press (UK&US).
34. Schneider, S.H. and S.L. Thompson, *Atmospheric CO_2 and climate: importance of the transient response.* Journal of Geophysical Research, 1981. **86**: p. 3135-3147.