Efficient Climate Policies under Technology and Climate Uncertainty – Appendix

Hermann Held*[†], Elmar Kriegler*[‡], Kai Lessmann*PIK authors and Ottmar Edenhofer*[§]

30th November 2008

A Utility quantile criterion

In the context of exploring alternatives to expected utility, we are currently investigating a utility quantile criterion under probabilistic uncertainty that is a promising candidate to provide important insight with respect to "robustness" of policies. The criterion is very flexible as it allows to continuously interpolate between a maximin (a pessimist's) and a maximax (an optimist's) criterion by a quantile parameter Q. Given the general interest in alternatives to expected utility, we present a definition of this form of "utility quantile optimisation" below:

$$\max_{I(\cdot)} U_Q(I(\cdot)) \quad \text{subject to} \tag{1}$$
$$\int_{U\in[U_Q(I(.)),\infty[} \mathrm{d}F_U(a; I(\cdot)) \geq 1 - Q, \qquad 0 < Q < 1$$

where $F_U(a; I(\cdot))$ denotes the probability distribution in utility space induced by the probability measure on a, and $U_Q(I(\cdot))$ the Q-quantile of this distribution. Maximin optimisation obtained in the limit $Q \to 0$, maximax optimisation for $Q \to 1$. For $Q > 0, Q \approx 0$ the utility quantile optimisation almost acts like maximin, however, disregards "a few, most extreme states of the world" that would drive a pessimist to accept very high expected losses in a model that is very nonlinear. First results indicate that under $Q \ll 1$ optimisation, MIND behaves very similarly to expected utility optimisation. A systematic study of MIND's behaviour under quantile-based optimisation as proposed above will be published elsewhere.

*Potsdam Institute for Climate Impact Research, PO Box 60 12 03, D-14412 Potsdam, Germany

[†]held@pik-potsdam.de

[‡]Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA 15213, USA

[§]Technical University of Berlin, Straße des 17. Juni 135, 10623 Berlin, Germany

B The energy sector within MIND

Energy from fossil fuels is produced from fossil resources R and a separate capital stock using a CES technology. This capital stock for fossil energy generation is made up by investments from the budget of the macroeconomy. The required resources R are extracted by use of resource extraction capital K_{res} according to the equation

$$R(t) = \kappa_{\text{l}}(t)\,\kappa_{\text{s}}(t)\,K_{\text{res}}(t)$$

Resource extraction is subject to learning by doing effects, modelled by κ_{l}, and scarcity effects described by κ_{s}. Scarcity about fossil resources is the main determinant of their costs in MIND. The equations read:

$$\kappa_{\text{s}}(t) = \frac{\chi_1}{C_{\text{res}}(t)} \tag{2}$$

$$C_{\text{res}}(t) = \chi_1 + \chi_2 \left(\frac{CR_{\text{res}}(t)}{\chi_3}\right)^{\chi_4} \tag{3}$$

$$CR_{\text{res}}(t) = \int_{\tau}^{t} R(t')\,dt', \quad CR_{\text{res}}(\tau) = 0 \tag{4}$$

Eq. (2) simply indexes the productivity of extraction capital by the inverse of marginal extraction costs C_{res} in units of the inverse of initial costs $\chi_1 :=$ 113 \$/tC. Eq. (3) is adopted from Nordhaus and Boyer (2000). Once cumulative extraction CR_{res} reaches χ_3, marginal extractions costs have increased by $\chi_2 :=$ 700 \$/tC. The exponent $\chi_4 := 2$ determines the curvature of marginal extraction costs as a function of cumulative extraction, where values of $\chi_4 > 1$ imply slowly rising costs early on ($CR_{\text{res}} < \chi_3$) and a steeper cost increase for $CR_{\text{res}} > \chi_3$. Therefore, parameter χ_3 can be regarded as a proxy for the size of the resource base, and its default value is set to 3500 gigatons of carbon in MIND version 1.1. In the context of this study, we will treat χ_3 as uncertain parameter, and may call it – albeit somewhat oversimplifying – resource base in the following.

Energy from renewable sources is produced by operating the installed capacity K_{ren} (in Gigawatts) for an average of $FLH_{\text{ren}} := 2190$ full load hours per year, i.e.,

$$E_{\text{ren}}(t) = FLH_{\text{ren}}\,K_{\text{ren}}(t)\,.$$

An investment flow I_{ren} into the renewable energy sector is converted to installed capacity by multiplication with the productivity κ_{ren} (Eq. (5)), which is the inverse of the costs of capacity additions (Eq. (6)). Renewable energy installations exhibit a vintage structure described by weights ω that give the fraction of capacity remaining from past investments going back a total of $\Delta t = 30$ years.

$$K_{\text{ren}}(t) = \int_{t-\Delta t}^{t} \omega(t-t')\,\kappa_{\text{ren}}(t)\,I_{\text{ren}}(t)\,dt' \tag{5}$$

$$\kappa_{\text{ren}} = \left(c_{\text{ren}}(t) + c_{\text{floor}}\right)^{-1} \tag{6}$$

Costs of capacity additions are comprised by a reducible part c_{ren} subject to learning by doing and floor costs c_{floor} fixating the minimum cost of additional capacity. The choice of floor costs and initial costs $c_{\text{ren}}(t_0) + c_{\text{floor}}$ was informed by a survey of future energy scenarios Nakićenović and Riahi (2002) and assumed to be 500 \$/kW and 1200 \$/kW, respectively Edenhofer et al. (2005). Due to the vintage structure of capacities, learning effects are limited to the most recent capacity additions.

We assume that every doubling of cumulative installed capacity $CK_{\rm ren}$ lowers the reducible installation costs $c_{\rm ren}$ by a fraction expressed through the learning rate $\tilde{lr}$:

$$\begin{aligned} \mu_{\rm ren} &= -\frac{\ln(1-\tilde{lr})}{\ln 2} && (7) \\ c_{\rm ren}(t) &= c_{\rm ren}(t_0)\left(\frac{CK_{\rm ren}(t_0)}{CK_{\rm ren}(t)}\right)^{\mu_{\rm ren}} && (8) \\ CK_{\rm ren}(t) &= \int_{t_0}^{t} K_{\rm ren}(t)\,dt && (9) \end{aligned}$$

Due to the presence of the irreducible floor costs, the overall learning rate in the renewable energy sector $lr(t)$ is lower than $\tilde{lr}$, and will decrease with time when accumulating capacity. It can be easily checked that the learning rate in the initial period t_0 is given by

$$lr(t_0) = \frac{c_{\rm ren}(t_0)}{c_{\rm ren}(t_0) + c_{\rm floor}}\,\tilde{lr}\,. \quad (10)$$

In MIND versions 1.0/1.1, the learning rate for the reducible part of the installation costs was set to 15% (Edenhofer et al., 2005), implying an overall learning rate in the initial period of 8.75%. This choice was informed by the survey of future energy scenarios by Nakićenović and Riahi (2002). In addition to the assumption of floor costs, MIND penalises large additions of renewable energy capacity between adjacent time periods $t-1$ and t. The rationale is that learning effects are reduced if investments are increased too rapidly to be fully efficient. All these effects are captured in the following time-discrete equation in MIND:

$$\begin{aligned} &c_{{\rm ren},t} - c_{{\rm ren},t-1} = \\ &\qquad c_{{\rm ren},0}\, CK_{{\rm ren},0}^{\mu_{\rm ren}}\left(CK_{{\rm ren},t}^{-\mu_{\rm ren}} - CK_{{\rm ren},t-1}^{-\mu_{\rm ren}}\right) \times \left(\frac{CK_{{\rm ren},t-1}}{CK_{{\rm ren},t}}\right)^{\beta_{\rm ren}} \quad (11) \end{aligned}$$

Parameter $\beta_{\rm ren} := 0.4$ in Eq. (11) sees to it that the cost reduction due to learning by doing is diminished between adjacent time periods.

Carbon capture and storage (CCS) technologies are available to reduce emissions from fossil fuel burning. To capture and store carbon dioxide (CO_2), sufficient capacities need to be built along the process chain comprising capture of CO_2 at point sources, transport via pipelines, compression, and injection into sequestration sites. MIND models each of these steps giving a choice of technological options.

MIND does not include artificial inertia constraints to limit the pace of transition between competing fossil and renewable technologies. Such inertia is introduced in a more intuitive way by (1) the vintage structure of the renewable energy sector, (2) the efficiency penalty on rapid increases in renewable energy capacity, and (3) the presence of fossil capital that generally will be used to the end of its lifetime in efficient solutions. However, the inclusion of the CCS sector gives the model the ability to rapidly reduce CO_2 emissions after an initial investment phase, if mandated by a very stringent climate target.

C The climate module within MIND

The climate module calculates the temperature response to anthropogenic forcing. Following Richels et al. (2004) we choose as temperature equation

$$\frac{dT}{dt} = \mu \ (\ln c - f_{\mathrm{SO_2}} - f_{\mathrm{OGHG}}) \quad - \quad \alpha \ T. \tag{12}$$

Hereby T denotes global mean temperature anomaly, t time, μ the radiative forcing for a doubling of preindustrial atmospheric CO_2 content divided by the heat capacity of the ocean (dominating the inertia of the climate system) and $\ln 2$, c the atmospheric carbon dioxide concentration in units of the pre-industrial level of 280 ppm, $f_{\mathrm{SO_2}}$ the sulphur forcing, f_{OGHG} the prescribed forcing due to other greenhouse gases and aerosols (both forcings in units of the $2{\times}CO_2$ forcing divided by $\ln 2$), and finally α the rate by which the climate would respond to changes in radiative forcing. c is derived from carbon emissions through a linear differential equation describing atmospheric accumulation and decay. In this study, we allow for uncertainty in the parameters μ and α determining the transient as well as equilibrium temperature response.

The climate module represents the simplest model possible to analyse the response of the climate system to carbon emissions. It is suitable for conceptual comparative studies like the present article. However, it should be replaced by a more advanced model when a quantitative assessment for policy advice is to be provided. In particular, the accumulation of carbon in the atmosphere may be underestimated for concentrations exceeding twice the preindustrial value. Otherwise, for temperature excursions up to 2° as studied here, the concentration and temperature response is captured qualitatively well[1].

D Parameter uncertainty and sampling strategy

As indicated in the previous section, we consider uncertainty about two key parameters in the energy system model of MIND, as well as uncertainty about two key parameters in the climate module.

D.1 Uncertainties in the energy system

Within the energy system we allow for uncertainty about (1) the "fossil resource base parameter" χ_3 (see Eq. (3)) and (2) the learning rate of the generic renewable energy technology. The later quantity is affected by uncertainty about the floor costs c_{floor} and the learning rate $\tilde{lr}$ for the reducible part of capacity additions (see Eq. (10)). Those parameters are poorly constrained by available information, but constitute key determinants of future fossil fuel extraction (χ_3) and the potential of renewable energy to provide a cost-effective alternative (c_{floor}, $\tilde{lr}$). Sensitivity studies of the model response to variations in χ_3 and $\tilde{lr}$ have been published in Edenhofer et al. (2006). Here, we specify subjective probability distributions[2] for the fossil resource parameter (χ_3) and the learning

[1]The temperature equation represents a perturbation approach for excursions out of a "hypothetical" pre-industrial climate equilibrium state. For a more specific justification of utilising just one single time scale for the transient climate response, see Appendix E.

[2]Subjective probabilities emerge in the Bayesian paradigm and reflect degrees of belief, not limiting frequencies. The notion of subjectiveness refers to the status of probability as

rate of a generic renewable energy technology (c_{floor}, $\tilde{lr}$) that are informed by the literature.

In the case of χ_3, we base our probability assessment on three different resource base estimates by Nakićenović (1996) (3500 GtC, used as default value in MIND version 1.1), Rogner (2000) (6500 GtC) and Moomaw and Moreira (2001) (5000 GtC). Based on these estimates, we derive a beta-distribution for $\chi_3 \in [\underline{\chi}_3, \overline{\chi}_3]$,

$$\rho(\chi_3) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \left(\frac{\chi_3 - \underline{\chi}_3}{\overline{\chi}_3 - \underline{\chi}_3}\right)^{\alpha-1} \left(\frac{\overline{\chi}_3 - \chi_3}{\overline{\chi}_3 - \underline{\chi}_3}\right)^{\beta-1} \frac{1}{\overline{\chi}_3 - \underline{\chi}_3}, \tag{13}$$

where the four degrees of freedom are fixed by the following assumptions:

1. the mean of the distribution falls on the medium estimate of 5000 GtC by Moomaw and Moreira (2001),

2. the distribution is left-skewed allocating more probability mass to resource bases above the mean. Accordingly, the mode is chosen to lie at 5750 GtC, the average of the estimates by Moomaw and Moreira (2001) and Rogner (2000),

3. on the lower end, the estimate of 3500 GtC by Nakićenović (1996) shall represent the 15% quantile of the distribution,

4. and the lower tail of the distribution shall extend down to $\underline{\chi}_3$:=2000 GtC.

These assumptions are fulfilled for values of $\alpha := 1.78$, $\beta := 1.30$ and $\overline{\chi}_3$:=7190 GtC. Fig. 1 shows the resulting cumulative beta-distribution for the fossil resource base χ_3 along with ten points sampled from it.

For describing the uncertainty about the learning rate of a generic renewable energy technology that can serve as backstop technology in the long run, we draw on Grübler and Gritsevskyi (2002) and Nakićenović and Riahi (2002). The first reference characterises the uncertainty by introducing three generic technologies with learning rates of 0, 10% and 20%, representing nil, moderate and rapid learners, respectively. The second reference describes a set of scenarios for average learning rates in the 21st century that reach up to 28% (solar PV), 12% (wind) and 13% (biomass) (Table 7 Nakićenović and Riahi, 2002). In this paper, we err on the conservative side by focusing on the learning rates of the more established, moderate learners among the renewables, and assume a normally distributed learning rate of the generic renewable energy backstop technology with expected value of 10%, and a 75% quantile of 12.5% (the average of the upper bound of biomass and wind learning rates from the scenarios discussed in Nakićenović and Riahi (2002)). In our model MIND, the average learning rate of renewables in the 21st century will be path-dependent due to the presence of floor costs. Therefore, we refer the above probability assessment to the learning rate in the initial period $lr(t_0)$ which is solely a function of the learning rate $\tilde{lr}$

expression of genuine belief, but does not imply biased or distorted belief statements. Ideally, informed and well-founded subjective probabilities are assessed via an elicitation of experts in the field. Since such expert estimates do not exist for the energy system parameters investigated here, and we wish to focus on the methodological side of analysing cost-effective mitigation policies under uncertainty, we specify our own subjective probabilities based on information from the literature.

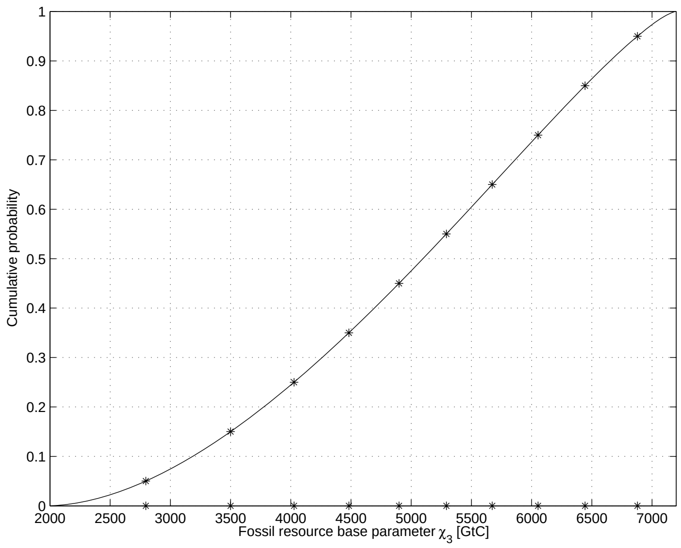

Figure 1: Sampling of the fossil resource base parameter. We choose equidistant sampling with respect to to the prior measure (depicted as cumulative density function at the ordinate).

for the reducible costs of capacity additions and the fraction of the floor costs relative to the initial costs (see Eq. (10)). Hence, our subjective probability estimate for $lr(t_0)$ is given by the normal distribution $N(0.1, 0.037)$.

For the sake of keeping the analysis simple, we fully correlate the variation in floor costs c_{floor} and learning rate of reducible costs $\tilde{lr}$ in a way that reflects our uncertainty assessment about $lr(t_0)$. This is achieved by making the following heuristic assumption:

$$\left(\frac{lr(t_0)}{lr_{\text{D}}(t_0)}\right)^{0.25} = 1 + \frac{c_{\text{floor,D}} - c_{\text{floor}}}{c_{\text{ren,D}}(t_0)} \tag{14}$$

$$\left(\frac{lr(t_0)}{lr_{\text{D}}(t_0)}\right)^{0.75} = \frac{\tilde{lr}}{\tilde{lr}_{\text{D}}}, \tag{15}$$

where the MIND version 1.1 default values of $lr_{\text{D}}(t_0) := 8.75\%$, $\tilde{lr}_{\text{D}} = 15\%$, $c_{\text{floor,D}} = 500\$/\text{kW}$ and $c_{\text{ren,D}} = 700\$/\text{kW}$ serve as reference points. This assumption allows us to convert a sample of overall learning rates $lr(t_0)$ drawn from $N(0.1, 0.037)$ into an associated sample of duplets $(c_{\text{floor}}, \tilde{lr})$ which determines the learning dynamics in the renewable energy sector in MIND. Fig. 2 shows such a sample of duplets corresponding to the 5%, 15%, ..., 95% quantiles of our subjective probability distribution for $lr(t_0)$.

We have drawn samples from the probability distributions of χ_3 (of size $K = 10$) and $lr(t_0)$ (of size $L = 10$) according to a technique called descriptive sampling (Saliby, 1990). Descriptive sampling is similar to Latin Hypercube Sampling (LHS) in that it divides the uncertainty space in n hypercubes with equal probability weight, but deviates from LHS in that it does not make a random selection from each hypercube $1 \leq i \leq n$, but rather chooses the

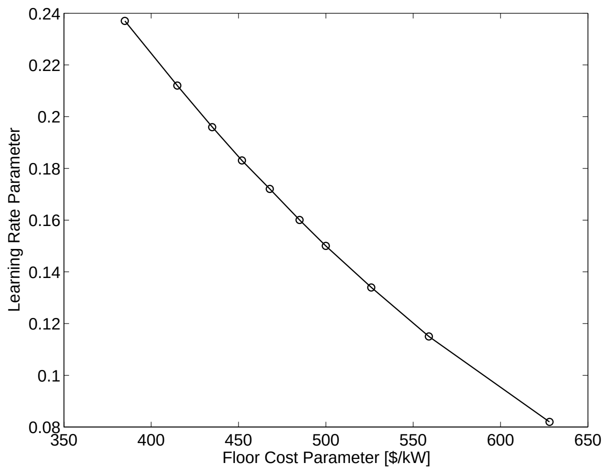

Figure 2: Coupled sampling of (initial) learning rate (of renewable energy technologies) and their floor costs.

$(i-0.5)/n$-quantile in a perfectly deterministic manner. Descriptive sampling has been shown to offer an improvement over LHS sampling in terms of estimator variance (Saliby, 1997). Concerns about biased estimates from descriptive sampling for highly varying response surfaces have lead to further development of the method Tari and Dahmani (2006). However, this is not an issue here since sensitivity analyses of MIND (e.g. in Bauer et al., 2005; Edenhofer et al., 2006) have shown that the macroeconomic response to variations in energy system parameters is smooth and without local extrema.

D.2 Uncertainties in the temperature response

Concerning the climate system, we allow for uncertainty about the parameters α and μ in temperature Eq. (12). However, we specify our prior probability distribution in another coordinate system that is more adjusted to the knowledge accumulated in the climate science community, i.e., a coordinate system spanned by *climate sensitivity* (CS) and the effective heat capacity of the ocean C_{oc}. CS is defined as the equilibrium response of T to a doubling of atmospheric CO_2 concentration relative to its preindustrial value (i.e., doubling c from 1 to 2). From Eq. (12), we conclude $\mathrm{CS} = (\ln 2)\mu/\alpha$. The ocean heat capacity C_{oc} is proportional to $1/\mu$ (Kriegler and Bruckner, 2004).

In the last six years, there have been numerous attempts to derive probability estimates for key parameters of the temperature response, in particular climate sensitivity. For this study, we have chosen to follow Frame et al. (2005) since (1) they use the same energy balance model (i.e. climate module) as utilised in MIND version 1.1, and (2) they present probabilistic information on the joint 2D parameter space of that model, consisting in a 5% likelihood contour (in percent of the maximum likelihood) in the joint CS-C_{oc} parameter space. The likelihood contour is derived by using patterns from HadCM3, a state of the art coupled ocean-atmosphere general circulation model, to distinguish carbon dioxide and sulphur dioxide forcing effects in the 20th century temperature record, and then

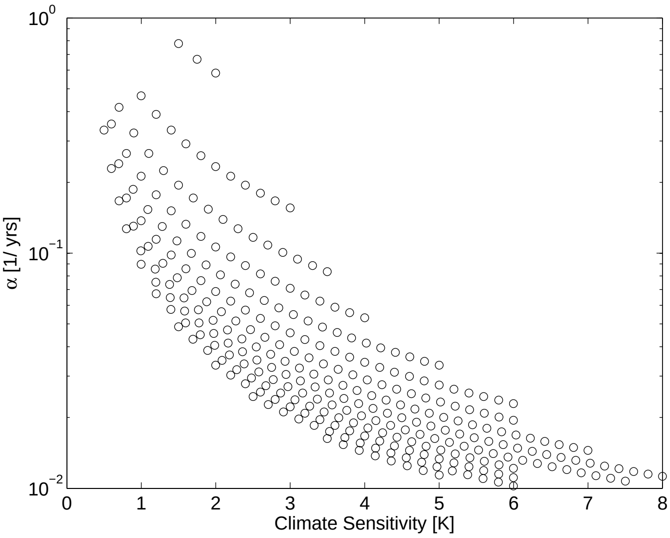

Figure 3: Sample of correlated climate parameters, nonlinearly transformed from a uniform sample in CS-C_{oc}-space.

comparing the filtered signal with the output of their energy balance model. We decided to proceed with this likelihood contour, pragmatically disregarding parameter combinations outside of its volume, and then assuming a uniform prior distribution over the remaining area in CS-C_{oc}-space. In this way, we include dependencies between climate sensitivity and ocean heat capacity that are induced by the 20th century temperature record.

In line with the assumption of a uniform prior, we chose equidistant sampling on the C_{oc}-axis and equidistant sampling of CS conditioned on C_{oc} to observe the boundaries of the confidence volume. This gives us a sample of $M = 301$ (CS,C_{oc}) combinations. However, as for the coupled economy-climate dynamics time scales are key, we find it instructive to present the sample equivalently in CS-α-space, as α represents the rate at which the climate system would respond to anthropogenic forcing – the second important system property one needs in addition the equilibrium property CS (see Fig. 3).

One may ask how the so derived distribution related to probabilistic information on CS as assembled in IPCC (2007), Ch. 9 (e.g. Fig. 9.20) and 10. Fig. **??** compares the projection of our distribution on CS with probability density functions from the IPCC report in thin lines, that are reported there in non- weighted a manner. We observe that our somewhat ad hoc reconstruction embraces a major fraction of distributions from the IPCC report.

To further sharpen our assessment of the joint probability on CS and effective ocean heat capacity we include a likelihood function for climate sensitivity that was derived from temperature data for the Last Glacial Maximum (LGM, approximately 21000 years ago), based on a study by Schneider von Deimling et al. (2006). In that work, the large temperature to carbon dioxide signal between LGM and modern day climate was assessed in a dynamically consistent way using a climate model of intermediate complexity, thereby providing

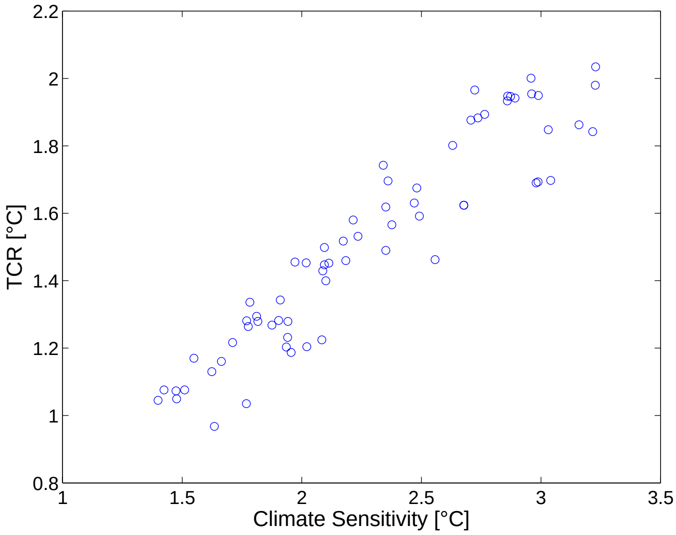

Figure 4: Uncertainty in transient climate response can predominantly be explained by climate sensitivity according to a uncertainty experiment with a complex climate model Schneider von Deimling et al. (2006). The remaining uncertainty must stem from uncertainty on time scales.

new constraints on CS. The LGM data provide a new source of independent information that has been represented as an additional Gaussian likelihood on CS of mean 3.06°C and standard deviation 0.907°C (Schneider von Deimling et al., 2006). In Fig. 6 of the main part we display our marginal pdf on CS after including LGM information by a bold solid line. It is apparent that the learning effect from LGM data is considerable. It can also be seen that the community's knowledge on CS can hardly be represented by a single pdf at present. We nevertheless proceed with the choice of a single pdf as required for our demonstration of an expected utility analysis of climate policies under chance constraints.

E Details on the uncertainty analysis of the climate module

E.1 Justification of choosing only one T time scale

The climate module, containing only one single time scale $1/\alpha$ is the simplest possible when considering transient climate responses on external forcing. However we feel that for the semi-quantitative analysis performed in this article such a module is sufficiently complex, for the following reason: uncertainty analyses with a climate model of intermediate complexity (i.e. on the order of thousands of prognostic variables (as against three in the present module; Schneider von Deimling et al. 2006)) reveal that uncertainty transient climate response is predominantly governed by uncertainty in climate sensitivity. The latter explains roughly 3/4 of response uncertainty (see Fig. 4; the "transient climate response

(TCR) displayed there is defined as the global mean temperature one obtains when forcing the climate module by a carbon dioxide concentration that increases with 1%/yr from pre-industrial levels, until it reaches twice that level), the remaining uncertainty stems from uncertainties in time scales. Here we argue that considering not uncertainty in climate sensitivity in isolation, but the joint probability of climate sensitivity and the most important time scale represents the next- important step of accuracy and transgresses considerations of the latest IPCC report (IPCC, 2007). Given that only 1/4 of the signal remain to be explained, choosing one time scale appears as just about right.

E.2 Interpreting our emission paths in view of IPCC probability density functions for CS

One may ask to what degree the emission paths that we derived would observe the 2DC temperature guardrail when various probability density functions for CS cited in the latest IPCC report were utilised. As the strength of our approach lies in a joint pdf for CS and response time scale, and this information is not provided in the IPCC report, we proceed in the following way: per pdf taken from the IPCC report we rescale our joint pdf such that the marginal in CS equals that of the IPCC's while the conditional distribution $p(\alpha|\mathrm{CS})$ stays invariant. Thereby we can still utilise a correlation structure between CS and time scale.

This is accomplished by the following numerical procedure: (1) fit a pdf into our marginal distribution $\mathrm{pdf}_0(.)$ for CS, made-up by 301 ensemble members by constructing a 10-bin histogram, that we then cubically interpolate and renormalise to 1, (2) any member of the 301-shot climate ensemble 1...m...301 gets weighted (in addition to learning from LGM) by the ratio $\mathrm{pdf}_{\mathrm{IPCC}}(\mathrm{CS}_m)$ $/\mathrm{pdf}_0(\mathrm{CS}_m)$, (3) the weighted ensemble is renormalised to 1.

The probability density functions on climate sensitivity reported in IPCC (2007) stem from Andronova and Schlesinger (2001); Forest et al. (2002, 2006); Frame et al. (2005); Gregory et al. (2002); Hegerl et al. (2006); Knutti et al. (2002, 2005); Piani et al. (2005).

E.3 Table of the climate parameter ensemble

The climate parameter ensemble is set up by uniform sampling of $1/\mu-$CS-space within the 5% likelihood contour given by Frame et al. (2005), Fig. 1a. We sample $1/\mu$ equidistantly and derive for each given $\mu_{m'}$ an equidistant set $\mathrm{CS}_{m'.1}$, ..., $\mathrm{CS}_{m'.m''}$, ...$\mathrm{CS}_{m'.M''(m')}$:

m'	$1/\mu_{m'}$ [yr/°C]	$\mathrm{CS}_{m'.1}$ [°C]	$\mathrm{CS}_{m'.M''(m')}$ [°C]	$M''(m')$
1	0.593634	1.5	2	3
2	1.48409	1	3	11
3	2.37454	0.7	3.5	15
4	3.265	0.6	4	18
5	4.15545	0.5	5	24
6	5.04589	0.6	6	28
7	5.93634	0.7	6	28
8	6.82682	0.8	7	33
9	7.71724	1	8	37
10	8.6077	1.2	7.5	33
11	9.49821	1.5	6	24
12	10.3886	2	6	21
13	11.2791	2.5	6	18
14	12.1695	3.5	5	8

α is diagnosed from (CS, μ) through CS=(ln2)μ/α (Kriegler and Bruckner, 2004).

F A 3×3 sensitivity experiment with quantile-adjusted climate sensitivity

One may ask whether it is really necessary to utilise the demanding chance constrained programming, whether not by adjusting just climate sensitivity (and climate response time scale $1/\alpha$, correlated with CS, accordingly) approximative results could be obtained from a simple deterministic approach.

We find that for our marginal distribution for CS (including LGM) the lower P^* =75%-quantile is 3.646 °C. The chosen values for α[1/yrs] are (1.562, 2.463, 5.821) $\cdot 10^{-2}$, the first and last component resulting from the extreme values, of (CS,α)'s support, given CS=3.646 °C.

The technology dimensions we correlate as follows

m	$\tilde{lr}_m$	$c_{\mathrm{floor}.m}$ \$/kW	$\chi_{3.m}$ GtC
1	0.082	628	6878
2	0.160	486	4837
3	0.237	385	2796

References

Andronova, N. G. and M. E. Schlesinger (2001). Objective estimation of the probability density function for climate sensitivity. *Journal of Geophysical Research 106*(D 19), 22,605–22,611.

Bauer, N., O. Edenhofer, H. Held, and E. Kriegler (2005). Uncertainty of the role of carbon capturing and sequestration within climate change mitigation strategies. In E. Rubin, D. W. Keith, and C. F. Gilboy (Eds.), *Proceedings of 7th International Conference on Greenhouse Gas Control Technologies (Vancouver, Sep 5-9, 2004)*, Volume 1: Peer-Reviewed Paper and Plenary Presentations, pp. 931–939. Cheltenham, UK.

Edenhofer, O., N. Bauer, and E. Kriegler (2005). The impact of technological change on climate protection and welfare – insights from the model MIND. *Ecological Economics 54*, 277–292.

Edenhofer, O., K. Lessmann, and N. Bauer (2006). Mitigation strategies and costs of climate protection: The effects of ETC in the hybrid model MIND. *Energy Journal Special Issue: Endogenous Technological Change and the Economics of Atmospheric Stabilization*, 89–104.

Forest, C. E., P. H. Stone, and A. P. Sokolov (2006). Estimated pdfs of climate system properties including natural and anthropogenic forcings. *Geophysical Research Letters*, L01705.

Forest, C. E., P. H. Stone, A. P. Sokolov, M. R. Allen, and M. D. Webster (2002). Quantifying uncertainties in climate system properties with the use of recent climate observations. *Science 295*(5552), 113–117.

Frame, D. J., B. B. B. Booth, J. A. Kettleborough, D. A. Stainforth, J. M. Gregory, M. Collins, and M. R. Allen (2005). Constraining climate forecasts: The role of prior assumptions. *Geophysical Research Letters 32*, L09702.

Gregory, J. M., R. J. Stouffer, S. C. B. Raper, P. A. Stott, and N. A. Rayner (2002). An observationally based estimate of the climate sensitivity. *Journal of Climate 15*(22), 3117–3121.

Grübler, A. and A. Gritsevskyi (2002). A model of endogenous technological change through uncertain return on innovation. In A. Grübler, N. Nakićenović, and W. D. Nordhaus (Eds.), *Technological Change and the Environment*. Resources for the Future, Washington, DC, USA.

Hegerl, G. C., T. Crowley, W. T. Hyde, and D. Frame (2006). Climate sensitivity constrained by temperature. *Nature 440*.

IPCC (2007). *Climate Change 2007: The Physical Science Basis*. Contribution of Working Group I to the Fourth Assessment Report of the IPCC. Cambridge University Press, Cambridge.

Knutti, R., F. Joos, S. A. Müller, and G. Plattner (2005). Probabilistic climate change projections for CO_2 stabilization profiles. *Geophysical Research Letters 32*, L20707.

Knutti, R., T. F. Stocker, F. Joos, and G. Plattner (2002). Constraints on radiative forcing and future climate change from observations and climate model ensembles. *Nature 416*, 719–723.

Kriegler, E. and T. Bruckner (2004). Sensitivity analysis of emission corridors for the 21^{st} century. *Climatic Change 66*, 345–387.

Moomaw, W. R. and J. R. Moreira (2001). Technological and economic potential of greenhouse gas emissions reduction. In B. Metz, O. Davidson, R. Swart, and J. Pan (Eds.), *Climate Change 2001: Mitigation*, Contribution of Working Group III to the Third Assessment Report of the IPCC, pp. 167–277. Cambridge University Press, Cambridge.

Nakićenović, N. (1996). Energy primer. In J. Bruce, H. Lee, and M. Haites (Eds.), *Climate Change 1995: Impacts, Adaptation and Mitigation of Climate Change*, Contribution of Working Group II to the Second Assessment Report of the IPCC, pp. 75–92. Cambridge University Press, Cambridge.

Nakićenović, N. and K. Riahi (2002). An assessment of technological change across selected energy scenarios. *IIASA-Report RR-2-005, IIASA, Laxenburg*, www.iiasa.ac.at/Admin/PUB/Documents/RP–02–005.pdf.

Nordhaus, W. D. and J. Boyer (2000). *Warming the world*. The MIT Press.

Piani, C., D. J. Frame, D. A. Stainforth, and M. R. Allen (2005). Constraints onclimate change from a multi-thousand member ensemble of simulations. *Geophysical Research Letters 32*, L23825.

Richels, R. G., A. S. Manne, and T. M. L. Wigley (2004). Moving beyond concentrations: The challenge of limiting temperature change. *AEI-Brookings joint center for regulatory studies 04-11*.

Rogner, H. H. (2000). Energy resources. In J. Goldenberg (Ed.), *World Energy Assessment: Energy and the Challenge of Sustainability*, pp. 135–171. Cambridge: United Nations Development Program (UNDP), United Nations Department of Economic and Social Affairs (UN-DESA) and World Energy Council (WEC).

Saliby, E. (1990). Descriptive Sampling: A better approach to Monte Carlo simulation. *The Journal of the Operational Research Society 41*, 1133–1142.

Saliby, E. (1997). Descriptive Sampling: An improvement over Latin Hypercube Sampling. *Winter Simulation Conference Proceedings*, 230–233.

Schneider von Deimling, T., H. Held, A. Ganopolski, and S. Rahmstorf (2006). Climate sensitivity estimated from ensemble simulations of glacial climates. *Climate Dynamics 27*, 463–483; DOI 10.1007/s00382–006–0126–8.

Tari, M. and A. Dahmani (2006). Refined Descriptive Sampling: A better approach to Monte Carlo simulation. *Simulation Modelling Practice and Theory 14*, 143–160.