Selection of Climate Policies under the Uncertainties in the Fifth Assessment Report of the IPCC

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Abstract

Strategies for dealing with climate change must incorporate and quantify all the relevant uncertainties, and be designed to manage the resulting risks[15]. In this paper, we employ the best available knowledge to date, summarized by the three working groups of the 5th assessment report of the Intergovernmental Panel on Climate Change (IPCC AR5)[5,7,25], to quantify uncertainty of mitigation costs, climate change dynamics, and economic damages for alternative carbon budgets. We rank climate policies according to different decision-making criteria concerning uncertainty, risk aversion, and inter-temporal preferences. Our findings show that preferences over uncertainties are as important as the choice of the widely discussed time discount factor. Climate policies consistent with 2°C are compatible with a subset of decision-making criteria and some model parametrizations, but not with the commonly adopted expected utility framework.

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Many of the uncertainties surrounding climate change are difficult to quantify and depend on the judgement of experts and on the type of models used to generate future scenarios. Each model produces a distribution over the possible states of nature (e.g. cost of mitigation, temperature increase, or economic damages from climate change), and these distributions might differ from model to model. How should we select climate policy in the face of these uncertainties?

This paper adresses this question using a framework that accounts for both state uncertainty (e.g. the distribution over states of nature) and model uncertainty (e.g. the different models (or experts) which generate distributions over states)[4].We investigate a variety of preferences and assumptions over these two types of uncertainties. A special case is the subjective expected utility[23] framework, traditionally used in economic evaluations. However, an expected utility setting might not work when the information is incomplete and ambiguous, which is clearly the case for climate change[9]. Moreover, people are known to approach risks and uncertainties differently[6]. The proposed setting allows us to explore additional decision-making criteria to deal with uncertainty, in the spirit of[9,17]. Alternative statistical techniques, consistent with Bayesian approaches, have been developed to cope with model uncertainty[8]. Model weighting in an active topic in climate research[28], where historical observations provide a basis for model evaluation, though it is not commonly used[13]. Though, our framework is sufficiently flexible to accommodate different prior probability measure over the set of possible models, our baseline model assumes a uniform prior with equal model weights.

The literature on the role of uncertainty in climate policy making has mostly relied on either analytical or simplified integrated assessment models (IAMs), such as DICE[20]. In such contexts, different decision-making criteria and preferences over risks have been shown to have a significant impact on the optimal abatement strategy[2,19]. However, these exercises lack detail in the representation of the mitigation options and of the climate dynamics. Larger scale models, which capture the main interrelationships between human and natural systems have incorporated uncertainty only partially due to computational limitations. Therefore, uncertainty is mostly treated by means of multi-model ensembles[14,26], or by single models performing Monte-Carlo simulations[3,22]. When accounting for all the key sources of uncertainty, the selection of optimal climate policy has been shown to be more sensitive to uncertainty about mitigation costs and impacts than to uncertainty about warming[16].

Figure 1 illustrates our approach. Using the best available knowledge from the three working groups of IPCC's AR5 (see Methods), for each component (mitigation costs, temperature, and climate damages) we generate probability estimates for different classes of models. The decision variable is the carbon budget, that is, the cumulative CO_2 emissions over the 21st century (2010–2100). Carbon budgets are robust policy indicators since they are strictly related to global warming[18] and climate targets[24]. We assume that uncertainty resolves immediately, but show that our results are robust to different timing of resolution of uncertainty (in the Supplementary Information Figure S12).

We extract emission projections and associated mitigation costs from the

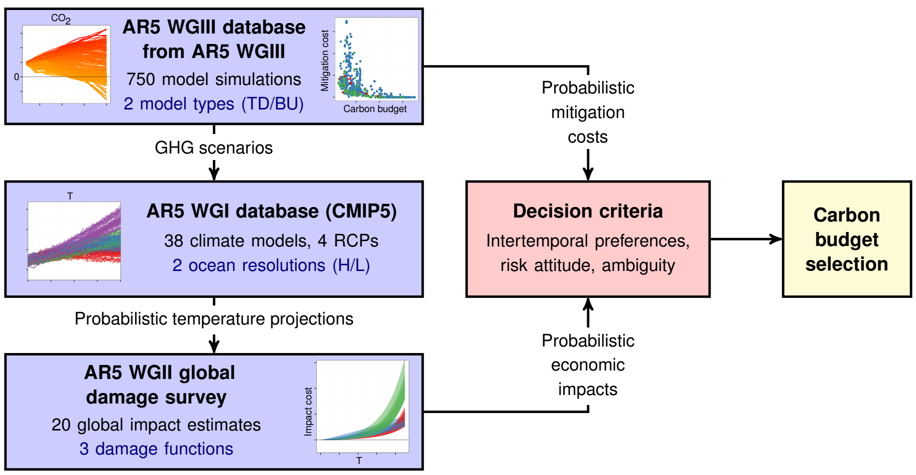

Figure 1: **Diagram illustrating the methodology.** Greenhouse gas emission scenarios and mitigation costs are extracted from the IPCC fifth assessment report, third working group (AR5 WGIII) scenario dataset. Temperature projections are computed from the fifth phase of the coupled model inter-comparison project (CMIP5) runs of the first working group (AR5 WGI) outcomes. Global economic impacts are generated on the basis of the impact reviews proposed in the fifth assessment report, second working group (AR5 WGII). Finally, carbon budgets are selected from a set of decision rules and preferences. For more details, refer to Methods.

AR5 WGIII Scenario database[5], which includes the outcomes of many long-term scenarios produced by the most well-established IAMs. The database spans a wide range of policy stringency, and thus of associated carbon budgets, covering the whole range of the representative concentration pathways. The relation between mitigation costs, harmonized across different metrics, and carbon budgets, is found to be non-linear and highly uncertain (SI Figure S2). Furthermore, the uncertainty of mitigation costs is increasing in time (SI Figure S3). From SI Figure S2 emerges a well documented[5] distinction between different classes of IAMs: top-down models (TD) provide a more accurate description of the economy, whereas bottom-up (BU) models better represent the set of mitigation technologies. TD generally show higher mitigation costs than BU, but it is not obvious which class is the most reliable. We account for this model type uncertainty by estimating different probabilistic models of the evolution of mitigation costs.

The second step is to generate probabilistic temperature projections for each emission scenario. The projections are generated by a probabilistic climate model based on a reduced complexity climate model[29] calibrated to emulate the temperature projections from the fifth phase of the coupled model intercomparison project (CMIP5)[27]. In addition to the whole set of CMIP5 dataset, we distinguish two classes of climate models: high and low resolution in the modelling of ocean dynamics, which give significant difference temperature projection at the end of the 21st century (see SI Figures S5 and S6). This allows us to account for climate-model uncertainty.

Finally, we link temperature increases to global economic impact using data reported in the AR5 WGII[7]. These estimates do not include all the potential damage from climate change[1,21], but represent the best currently available knowledge and have been used for calculating the social cost of carbon[11]. Given the weak theoretical and empirical consensus on the functional form of the relationship between temperature increase and damage, and the few estimates available, especially for temperatures above 3°C, we capture model uncertainty by calibrating three damage models of the impact distributions. In addition to the commonly used quadratic specification, we also consider exponential and sextic impact functions (SI Figure S7).

Each carbon budget can be associated to time-dependent distributions of payoffs (Figure 2). In the case of a very stringent carbon budget (left panel), climate damages are kept under reasonable control, and both the damage function and the climate resolution model have a negligible impact on GDP. Rather, it is the mitigation-cost uncertainty that has a sizeable impact on the mean, while the tails are affected by the choice of the damage model. The right-hand side panel presents the results of a significantly higher carbon budget. In this case, model uncertainty regarding damages has huge implications on both the mean and the tails. As this higher budget is consistent with very low mitigation effort, neither model uncertainty nor state uncertainty related to mitigation costs have any significant influence. Climate model uncertainty appears to play a lesser role despite its significant impact on late-century temperature increase. Figure 2 also shows how the quadratic damage model, typically employed in

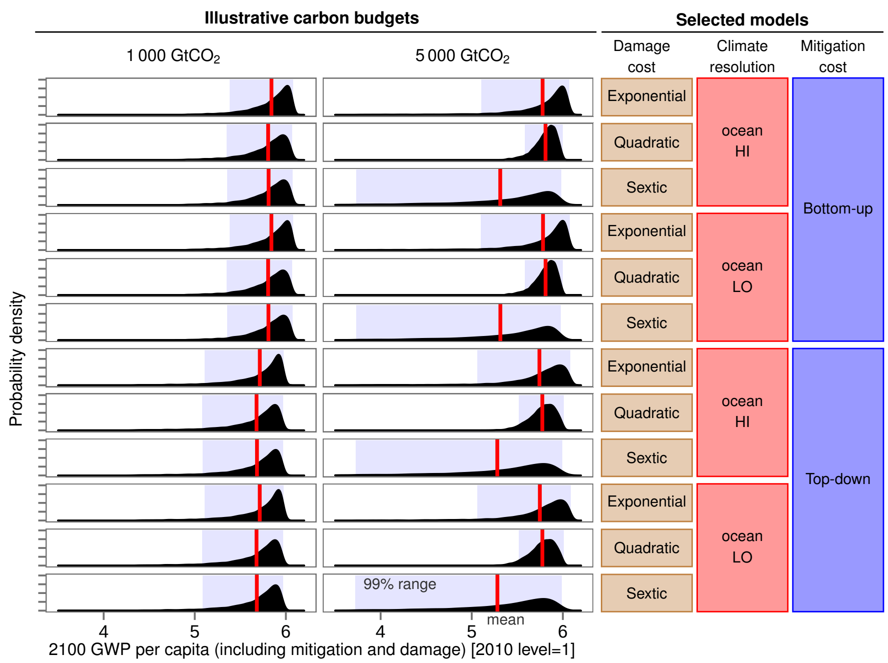

Figure 2: **Influence of carbon budgets, model and state uncertainties on the distribution of the gross world product (GWP) per capita in 2100.** The GWP per capita net of mitigation and damage costs is expressed relatively to its 2010 level. Results are provided for two illustrative and well distanced CO_2 carbon budgets (cumulative emissions over the period 2010–2100 of 1000, and 5000 $GtCO_2$). The distribution means are indicated by a red line, and 99% percentile ranges in blue shades. HI and LO stand for high and low resolution, respectively.

most cost-benefit analysis of climate policy[20], fails entirely to capture significant fat-tailed impact events, even when considering the uncertainty in climate response.

Given the distributions associated with different carbon budgets, to select climate policies, we use a flexible utility function which allows us to disentangle preferences over time, consumption smoothing, and risk. We specify three decision criteria. The first two criteria are built upon the "classical subjective expected utility" framework[4]. The *subjective expected utility* criterion (*SEU*) takes expectations over states of nature and over models (each considered equally likely). The *maxmin expected utility* criterion *(maxmin EU)* combines the expected utility with the maxmin criterion[30], effectively distinguishing between model and state uncertainty. The carbon budget is selected on the basis of the expected payoff of the most pessimistic model. Finally, we consider the *maxmin* criterion[30] in which the decision makers focus on the worst consumption per capita over both world states and models. Additional frameworks have been proposed, but the aforementioned ones are among the best known and provide useful benchmarks[9].

The selected carbon budgets for the three different decision criteria, as well as for preferences over time, intertemporal substitution, and risk are reported in Figure 3. Results confirm the relationship between time preference and climate policy, namely, that higher discounting of future payoffs leads to higher CO_2 budgets. A similar dynamics occurs with respect to the elasticity of intertemporal substitution (EIS), which measures the propensity to smooth consumption over time from future (richer) generations to current (poorer) ones.

The figure also allows us to quantify the role of preferences over model and state uncertainties. Aversion against model uncertainty (shown by the comparison between *SEU* and *Maxmin EU*) leads to significantly more stringent climate policies. Ambiguity about the damage function is the most important driver of model uncertainty, reflecting its highly unknown nature (SI Table S4). Aversion against state uncertainty has an ambiguous impact on climate policy: when the budgets are relatively high (e.g. because of high discounting or low EIS), higher risk aversion leads to more stringent carbon budgets, in order to avoid high climate change damages. The opposite happens at low budgets, due to the risks of high mitigation costs . Quantitatively, the impact of risk aversion is relatively modest. Finally, *maxmin* constitutes a limiting case of the *maxmin EU*: since the focus is exclusively on avoiding the worst outcomes, *maxmin* never leads to lenient climate policies; but it also avoids very stringent ones.

From a policy perspective, the impact of the choice of the decision-making criterion is shown to be as large as that of time discounting and consumption smoothing. The carbon budget across the decision criteria differs from 500 to almost 2000 $GtCO_2$, a major variation in climate policy stringency. Using the central estimates for the temperature climate response to emissions[25], this translates into a difference in warming of 0.25 to 1°C. Carbon budgets compatible with a radiative forcing of $2.6 W/m^2$ — which is associated with the 2°C target — are selected with some specifications; however, 2°C appears to never be optimal under the *SEU* criterion, which is the one employed in the vast

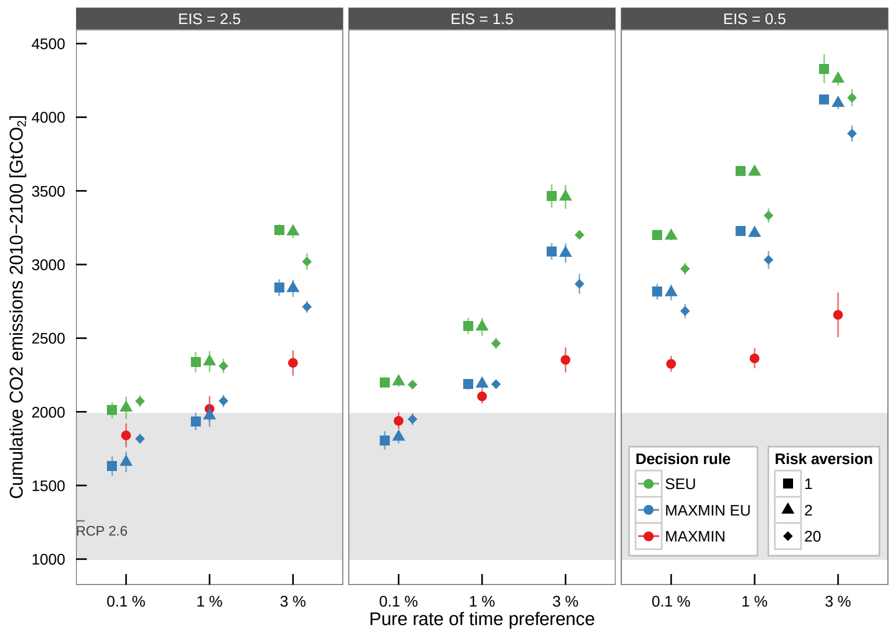

Figure 3: **Selected carbon budgets according to three decision-making criteria, relative risk aversion, consumption smoothing and pure rate of time preference**. The shaded area represents the carbon budget range compatible with a radiative forcing of $2.6\mathrm{W/m^2}$, according to Table SPM.3 of the IPCC AR5 from WGI[2]. The representative concentration pathway 2.6 carbon budget (RCP2.6) is also shown. The vertical bars represent the estimates of the standard errors using bootstrapping. EIS stands for elasticity of intertemporal substitution. Decision rules are Subjective Expected Utility (EU), Maxmin Expected Utility (MAXMIN EU) and Maxmin (MAXMIN).

majority of cost-benefit analyses of climate change.

Combining the vast amount of data and information collected in the AR5 with the recent advances in decision theory allows us to quantify the key uncertainties associated with climate change, and to propose a methodology for selecting global climate policies under different preference structures. We show that aversion to both model and state uncertainty has a major impact on the selection of policies, as a result of the scarcity of knowledge that is still prevalent in the literature on economic assessments of climate change[10]. Uncertainties reported in the AR5 are likely to be lower bounds for actual uncertainties, and are known to increase when moving from global scales to local ones[12]. This might suggest that additional precaution should be taken in devising our collective preferences. Our results point to the need for additional research to understand and better quantify a wider set of climate-change impacts. Similarly, mitigation-cost estimates are still very imprecise, and in many instances fail to include important economic feedback as well as ancillary benefits. Moreover, learning about uncertainties might yield insights on the dynamics of abatement.

So far, uncertainty has exacerbated the polarization in the public debate over climate change policies. On the one hand, uncertainty has been interpreted as a reason for limited action on climate, while on the other hand, it has been used as a precautionary argument in favour of stringent mitigation. This paper provides one of the few comprehensive approaches to uncertainty quantification in climate change. By helping decision-makers to see how their preferences translate into climate policy recommendations, frameworks such as ours can help improve the assessment of climate-change strategies.

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Methods

We propose a method for selecting climate policies which accounts for different preferences for risk, ambiguity, and time. We adopt a two-stage subjective expected utility framework[5] that accounts for both state and model uncertainty. In the context of this paper, "model uncertainty" refers to the existence of alternative modelling paradigms relating how mitigation costs, the dynamics of the climate system, or economic damages resulting from climate change might respond to climate policies; while "state uncertainty" refers to the probabilistic response (of mitigation costs, temperature, or climate damage) that each of these models produces given a climate policy.

Integrated Assessment Model dataset

The dataset is issued from the AR5 scenario database, which has been created for the Integrated Assessment Modeling Consortium (IAMC) and is hosted and maintained by the International Institute for Applied Systems Analysis (IIASA). This database is publicly available and contains outcomes from several model comparison projects, reviewed in the Fifth Assessment Report (AR5) of Working Group III of the Intergovernmental Panel on Climate Change (IPCC). The full description of the database is available in the dedicated website (`https://secure.iiasa.ac.at/web-apps/ene/AR5DB`) and in Section A.II.10 of the IPCC AR5).

The meta-analysis is carried out with a subset of the AR5 scenario database. We select those long-term scenario-model outcomes that meet the following criteria: (a) model time horizon goes up to the year 2100; (b) mitigation cost estimates are provided; (c) carbon dioxide CO_2, methane CH_4 and nitrous oxide N_2O emissions are provided; (d) climate policy category is "baseline", "reference", or "first best". "Baseline" scenarios imply no climate policy after 2010, "reference" scenarios implement a weak policy and current pledges, and "first best" scenarios have an efficient carbon policy with an immediate target adoption. This leaves us with outcomes from 8 integrated assessment models and 6 model inter-comparisons projects: The Asian Modeling Exercise (AME)[32], the Assessment of Climate Change Mitigation Pathways and Evaluation of the Robustness of Mitigation Cost Estimates (AMPERE) project[40], the Energy Modeling Forum's Climate Change Control Scenarios (EMF-22) and Global Model Comparison Exercise (EMF-27)[17],the Low climate IMpact scenarios and the Implications of required Tight emissions control Strategies (LIMITS) project[16] and the Roadmaps towards Sustainable Energy futures (ROSE) project[37]. For each scenario we extract the global emission pathway and the mitigation costs over the century.

Carbon budget

A carbon budget is defined as the cumulative total CO_2 emissions over the period 2010–2100. For each scenario, we sum up the world emissions of CO_2

from fossil-fuel combustion and industry, and from land-use change. As the database provides the annual emissions every 10 years from 2010 to 2100, the intermediary annual emissions are linearly interpolated (see SI Figure S1 for an overview of the emission pathways and the carbon budgets from the selected dataset).

Mitigation costs

Each scenario is associated with information on mitigation costs. "Baseline" scenarios have zero mitigation costs. Due to the different nature of the models, mitigation costs are expressed in three different, but comparable, cost metrics: (1) gross world product (GWP) losses, (2) area under the marginal abatement cost curve, and (3) additional total energy system cost. These costs are converted in % GWP change from baseline scenario. SI Figure S2 reports, for each scenario-model outcome, two dimensions: carbon budget and mitigation costs. Carbon budgets are negatively correlated with mitigation costs, in a non linear way.

Model categorization is based on a well documented distinction [34] between two classes of integrated assessment models: top down models (TD), which provide a more accurate description of the macroeconomic feedback, versus bottom up (BU) models, which better represent the set of mitigation technologies. For the purpose of mitigation costs, TD generally show higher costs than BU, but it is not obvious which class of models should be considered as the most accurate.

On the basis of this data, we estimate three piecewise probabilistic models relating, at each time period, carbon budgets and mitigation costs. The procedure, described in the subsequent paragraph, is the same for the three estimated models, what changes are the mitigation cost data used: (1) data only coming from TD models, (2) data only coming from BU models, and (3) the whole dataset. First, mitigation costs are clustered in five groups spanning the range of carbon budgets. We fit each cluster data with Weibull distributions. Second, we estimate, by means of least square, a relationship between the Weibull distribution parameters and the budgets (the central budget of each cluster is taken as a reference in the fitting). In all cases, each scenario-model outcome is weighted equally. SI Figure S3 presents the resulting piecewise probabilistic mitigation cost function for the case of the whole dataset.

Probabilistic temperature

We use an updated version of a climate model of reduced complexity[23], to emulate the CMIP5 model ensemble response. This model version is composed by a climate module DOECLIM [36] and a carbon cycle model which includes feedbacks from the atmospheric CO_2 concentration and temperature [41]. Key geophysical model parameters are estimated from the CMIP5 temperature projections from 2010 to 2100 using a Bayesian inversion technique based on the

Markov Chain Monte Carlo (MCMC) algorithm. The estimated climate parameters are the climate sensitivity, the heat vertical diffusivity in the ocean, and the aerosol scaling factor to the total radiative forcing. The carbon-cycle estimated parameters are the carbon fertilization from living plants, the respiration sensitivity related to temperature, and the thermocline carbon transfer rate in the ocean. Additionally, initial conditions of atmospheric temperature and CO_2 concentration are also estimated.

To perform the MCMC, we constrain the model with the temperature projections for the 4 Representative Concentration Pathways (RCP2.6, RCP4.5, RCP6.0 and RCP8.5) provided by 38 climate models in the CMIP5 dataset to constrain the model. We retain 5'000 equally distant combinations of parameters out of the 3'000'000 in the MCMC to avoid cross-correlation between them. The emulator is able to reproduce the spread of the temperature projections from the CMIP5 dataset for the 4 RCPs (see SI Figure S4).

It is difficult to distinguish different classes of models from the CMIP5 ensemble as "there is high confidence that the model performance for global mean surface air temperature (TAS) is high", where the level of confidence is a combination of the level of evidence and the degree of agreement (Section on model evaluation in the Chapter 9 of the AR5 WGI[2]). Our choice is to split the model outcomes into 2 classes according to the extent of ocean resolution of the climate model (more or less than 50'000 horizontal grid points). For the RCP4.5 and RCP 6.0, the CMIP5 model provides good agreement, while for the more extreme scenario RCP2.6 and RCP8.5, the two classes of models slightly diverge after 2070. In these cases, the high resolution models have a colder atmosphere in comparison to the low resolution models (see SI Figure S5). Applying the two-sample Welsh's t-test[47] on the two subsets of the data, the difference in yearly mean becomes highly significant after 2070 for the RCP2.6 and RCP8.5 (SI Figure S6).

Once calibrated, the emulator computes probabilistic temperature projections associated to each scenario-model outcome, given information on carbon dioxide emissions, radiative forcing of other greenhouse gases and of aerosols. The radiative forcing for the non-CO_2 greenhouse gases is taken from the database, when available, otherwise it is estimated from the emission level and their accumulation in the atmosphere. Similarly, the radiative forcing from aerosols is taken from the dataset, when available, otherwise it is inferred from the RCP database (available at `http://www.iiasa.ac.at/web-apps/tnt/RcpDb`). Three sets of projections are produced, one for each of the three probabilistic models (low, high ocean resolution, and the join set).

Probabilistic impacts of climate change

We use 20 estimates of total economic effects of climate change from the literature reviewd in Table 10.B.1 from the Chapter 10 of the IPCC WGII AR5[3]. These estimates have been calculated using a variety of methods, but they usually aggregate one by one the economic costs accruing in different sectors of both global and local impacts. Each study reports the mean estimates of the economic climate change damage for a given increase in global mean temperature. Five of the studies also include a measure of the uncertainty surrounding these estimates under the form of standard deviation (normal distribution) or a confidence interval (skewed distribution). In the case of the skewed distribution, we estimate the parameters of a displaced Gamma distribution matching the reported confidence interval and mean. Given the few data and given that studies only cover temperature increases of up to 4.8°C, we fit three different probabilistic damage models over the economic climate change damage data. Let I_d be the economic impacts, expressed in % of GWP, T be the temperature increase and β_j the regression coefficients, then the three impact functions are:

1. a quadratic impact function $I_1(T) = \beta_1 T + \beta_2 T^2$, as proposed by[43] and which has been used in the DICE integrated assessment model[13]. This function can allow for positive impacts (benefits) at low temperatures.
2. an exponential impact function $I_2(T) = \exp(-\beta_3 T^2) - 1$, as introduced by[45], which excludes the possibility of positive damage (benefits) and which implies greater losses at high warming levels.
3. a sextic impact function $I_3(T) = \beta_4 T^2 + \beta_5 T^6$, adapted from[46], which implies catastrophic outcomes at extreme temperatures.

The economic damage distributions generated by the three models are shown in SI Figure S7 as probabilistic functions of the temperature increase.

The procedure to estimate the probabilistic relationship between carbon budgets and damage costs is similar to the one used for generating the mitigation costs probabilistic models. First, we gather the generated damage costs in five clusters spanning the range of carbon budgets, and we fit each cluster data with a log-normal distribution. Second, we estimate, by means of least square fit, the relationships between the log-normal distribution parameters and the carbon budgets (using the central point of each cluster as a reference). However, in the case of damage, for each of the carbon budget we have three temperature probabilistic models and, associated to each temperature level, three damage functions. SI Figure S8 presents the three resulting piecewise probabilistic damage cost functions, for three illustrative years, using temperature projections based on the whole CMIP5 dataset model.

Economic projection

We use global projections of population and economic production growth produced by the Organisation for Economic Co-operation and Development (OECD) for the second Shared Socio-economic Pathway (SSP2)[38]. The SSP2 describes a "middle of the road" socio-economic scenario. Let $\bar{Y}_t$ denote production per capita for each year $t \in T = \{2010, \ldots, 2200\}$, gross of any mitigation or damage cost. At each time period t, given each state of the world s, and each of the mitigation and damage probabilistic models m, the overall economic impacts associated to a carbon budget c is given by the combination of the mitigation cost $M_t(c;s,m)$ and the climate change damages $D_t(c;s,m)$. Both mitigation and damage are indexed on the combination of models m, and m is defined as a triplet selected within the set Ω ={{mitigation-all, mitigation-BU, mitigation-TD}×{climate-all, climate-ocean-lo, climate-ocean-hi}× {{damage-sextic}, {damage-quadratic}, {damage-exponential}}}. The classes of model are listed in SI Table S1. As both mitigation and damage losses data are expressed as % of GWP, we can compute the resulting per capita world production net of mitigation and damage losses.

$$Y_t(c;s,m) = \bar{Y}_t \times (1 - M_t(c;s,m)) \times (1 - D_t(c;s,m)),\ \forall t \in T. \tag{1}$$

Given that outcomes from the dataset end in 2100, we assume that post-2100 mitigation costs decrease linearly, starting from their 2100 level to 0 in 2200, and that post-2100 damage costs remain constant at their 2100 level over the whole 22nd century.As an illustration, Figure 2 displays the distributions of $Y_t(c;s,m)$ in 2100, for twelve combinations of models ({{mitigation-BU, mitigation-TD}×{climate-ocean-lo, climate-ocean-hi}×{damage-sextic, damage-quadratic, damage-exponential}}) and for two carbon budgets. SI Figure S11 provides an inter-temporal view of $Y_t(c;s,m)$ for three representative budgets.

Consumption

Not all models included in the dataset report the value of global consumption. This is particularly true for bottom-up energy model. As we want to perform our calculation using utility which is generally a function of consumption, we need to translate GWP into consumption figures. For those models reporting both consumption and GWP, the ratio of the two measures remains constant across scenarios and presents a similar time trend, as depicted in SI Figure S9. We fit the model mean ratio with a quadratic function and extrapolate it until 2200 (SI Figure S10). The fitted ratio is 0.741 in 2020, which is consistent with the 26% world gross saving forecast for the year 2017 by the World Economic Outlook of the International Monetary Fund, slightly increasing over time (to 0.820 in 2200). This procedure allows us to express mitigation and damage losses in terms of consumption losses. In particular, to obtain consumption per capita, we apply the fitted ratio ζ_t to the world net production per capita at each time period.

$$C_t(c;s,m) = \zeta_t Y_t(c;s,m),\ \forall t \in T. \tag{2}$$

Utility function

To translate consumption per capita into utility, we employ the Epstein-Zin preferences formulation[33]. This formulation allows to disentange preferences over time, consumption smoothing and risk. The recursive utility function is

$$V_{t,\omega}(c;s,m) = \left[(1-\beta)C_t^{1-\rho}(c;s,m) + \beta\left(\mathbf{E}_{t;s,m} V_{t+1,\omega}^{1-\alpha}(c;s',m')\right)^{\frac{1-\rho}{1-\alpha}}\right]^{\frac{1}{1-\rho}}, \tag{3}$$

where $\mathbf{E}_{t;s',m'}$ is a time-dependent expectation operator over states, s, and models, $m \in \omega \subseteq \Omega$. α and β denote the relative risk aversion and the time preference parameter, respectively. $\beta = \frac{1}{1+\delta}$ and δ is the pure rate of time preference. ρ is the reciprocal of the elasticity of intertemporal substitution (EIS). In the first period $t_0 = 2010$, the equation 3 simplifies to

$$V_{t_0,\omega}(c) = \left[(1-\beta)C_{t_0}^{1-\rho} + \beta\left(\mathbf{E}_{s\in S,m\in\omega} V_{t_0+1,\omega}^{1-\alpha}(c;s,m)\right)^{\frac{1-\rho}{1-\alpha}}\right]^{\frac{1}{1-\rho}}, \tag{4}$$

where C_{t_0} denotes world consumption in 2010 which is known and independent of the carbon budget, c. The expectation operator $\mathbf{E}_{t_0} = \mathbf{E}_{s\in S,m\in\omega}$ is applied over the future states of the world S and over a subset of models ω. For $t > t_0$, the future state of the world is certain as well as the selected model, so equation 3 is written as

$$V_{t,\omega}(c;s,m) = \left[(1-\beta)C_t^{1-\rho}(c;s,m) + \beta\left(V_{t+1,\omega}^{1-\alpha}(c;s,m)\right)^{\frac{1-\rho}{1-\alpha}}\right]^{\frac{1}{1-\rho}}, \forall t > t_0. \tag{5}$$

Starting from the last period 2200, we compute the utility values recursively every year until 2010. We are assuming uncertainty resolves in period 2020, however, we provide a robustness analysis for different learning periods in the supplementary information. We specify a utility value of 0 for $t > 2200$.

Decision rules

We build up on the so-called "classical subjective expected utility" framework[5]. This framework allows us to disentangle two sources of uncertainty: "model" uncertainty, m and "state" uncertainty, s. We expand this framework to account for decision makers (DM) with different attitude towards "model" and "state" uncertainty. The decision rules are listed in SI Table S2 and explained hereafter.

Maxmin rule

According to the Maximin criterion, the DM is precautious and discards any probabilistic information. The DM's main objective is to avoid the worst case across both states and models. At each period of time, the DM considers only the worst world consumption per capita over both the states and model dimensions. The discounted utility is computed as follows

$$\mathcal{V}_t(c) = \left[(1-\beta)(\min_{s,m} C_t(c;s,m))^{1-\rho} + \beta\mathcal{V}_{t+1}^{1-\rho}(c)\right]^{\frac{1}{1-\rho}}. \tag{6}$$

Similarly to V, $\mathcal{V}_t(c) = 0$ for $t > 2200$. The DM selects the carbon budget which leads to the highest value for $\mathcal{V}_{t_0}(c)$.

Subjective Expected Utility

According to the subjective expected utility criterion, the DM considered "model" and "state" uncertainty as interchangeable and assumes all models are equally valid (as she does not have information to make any better judgment). The expectation operator aggregates over states and model combinations. In this case ω ={{mitigation-all}×{climate-all}×{damage-sextic, damage-quadratic, damage-exponential}} and

$$V_{t_0}(c) = \left[(1-\beta)C_{t_0}^{1-\rho} + \beta \left(\mathbf{E}_{s,m} V_{t+1}^{1-\alpha}(c;s,m)\right)^{\frac{1-\rho}{1-\alpha}}\right]^{\frac{1}{1-\rho}}. \tag{7}$$

This formulation is equivalent to the Savage's subjective expected utility decision criterion[5].

Maxmin Expected Utility

According to the Maxmin expected utility criterion, "model" and "state" uncertainty should be considered differently. In particular, the criterion is dogmatic about which of the model to consider and puts all the weight on the most pessimistic one, while for each of the models expected utility over states of the world is considered.

First, the utility associated with each possible combination of models $\omega = m \in$ {{mitigation-BU, mitigation-TD}×{climate-ocean-lo, climate-ocean-hi}×{damage-sextic, damage-quadratic, damage-exponential}} is calculated as:

$$V_{t_0,m}(c) = \left[(1-\beta)C_{t_0}^{1-\rho} + \beta \left(\mathbf{E}_{s} V_{t+1}^{1-\alpha}(c;s,m)\right)^{\frac{1-\rho}{1-\alpha}}\right]^{\frac{1}{1-\rho}}. \tag{8}$$

The Subjective Expected Utility and Maxmin Expected Utility frameworks incorporate, respectively, neutrality and full aversion to the ambiguity related to the specification of the data-generating model. The Maxmin Expected Utility criterion focuses on model uncertainty and should not be confused with the Maxmin Expected Utility with non-unique prior[35] which focuses on states of the world.

Carbon budget selection

We generate the policy and damage costs for 10'0000 stochastic worlds and 15 non trivial combinations of model choices, {{{mitigation-BU}, {mitigation-TD}} × {{climate-ocean-lo}, {climate-ocean-hi}} × {{damage-sextic}, {damage-quadratic}, {damage-exponential}}} + {{mitigation-all} × {climate-all} × {{damage-sextic}, {damage-quadratic}, {damage-exponential}}}, for 2'500 carbon budgets within the range 500–6000 $GtCO_2$. Criteria are computed for different δ, α, and ρ. Carbon budgets are selected at the maximum of a function, fitting the generated data by a local polynomial regression. We repeat these steps 5'000 times and estimate the error done in the carbon budget selection. The main results, including the estimated standard errors, are shown in SI Table S3 and Table S5.

Parameter specification

δ represents the pure rate of time preference. We use 3 values: 0.1%, 1% and 3%, which covers the spectrum of values used in climate policy analysis[39,42]. ρ represents the propensity to smooth consumption over time and is equal to the inverse of the elasticity of intertemporal substitution (EIS). The default value for EIS is $^3/_2$, with sensitivity to $^1/_2$ and $^5/_2$, as elicited in the literature[31,44]. α represents the coefficient of relative risk aversion, which we allow to range from 1 to 20. Bansal and Yaron[31] suggest a value of around 10.

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