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Climate policy under socio-economic scenario uncertainty☆

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ABSTRACT

We study the role of uncertainty about the two main baseline drivers of the economy, namely population and GDP, for the determination of the optimal climate policy and the evaluation of policy costs. Firstly, we estimate the cost of baseline uncertainty from a decision maker's perspective using different metrics. Secondly, we discuss how measures of the costs of climate change induced impacts and climate policy costs can be compared under different and uncertain baseline assumptions. Given that policy costs and other measures such as impacts are typically expressed relative to GDP in a baseline, comparing those values with different baseline projections is not trivial. Finally, we compute the cost from baseline uncertainty which leads to a moderate increase of the welfare losses from climate change.

1. Introduction

The role of uncertainty in the field of climate change has been widely studied in recent years. A focus of research has been the role of scientific uncertainty in the climate system, in particular the uncertainty about the climate sensitivity parameter (Rogelj et al., 2012; Urban et al., 2014). Secondly, the significant uncertainty around the estimates of economic impacts from climate change has been focused on, which has been prominently featured also in the latest IPCC report (Arent et al., 2014). Another field where uncertainty has entered the climate change debate has been the role of tipping points and the possibility of climate catastrophes being triggered by crossing a threshold in the climate systems (Weitzman, 2009; Lontzek et al., 2015). In all these cases, the source of uncertainty lies in the climate system or the biophysical impacts and their socio-economic evaluation (Dietz, 2012). The implication for decision-making in such circumstances has often been a more precautionary approach for optimal climate policy in such situations (Millner et al., 2013; Kunreuther et al., 2013; Drouet et al, 2015). Alternatively to the optimal policy, quantitative methods can be used to explore a large space of futures and select the "best" policy according to specific criteria (Chapman, 1984; Lempert et al., 2003).

In applied policy analysis, integrated assessment models (IAMs) compute estimates of the costs and benefits of climate change policies, and have been improved in the recent years to include these uncertainties (Crost and Traeger, 2014; Arrow et al., 2013). In addition to the calibration of the climate system representation and the climate impact functions, the IAMs also require the specification of a baseline scenario of population and GDP or productivity growth. A recent study demonstrates that the parametric uncertainty in these models is very important (Gillingham et al., 2015). The choice of this baseline scenario is then crucial as it is used as a reference point to derive the optimal abatement of emissions, the mitigation costs and the impacts from climate change. In practice, during model intercomparison exercises for IAMs, the models choose to harmonize their baseline in order to eliminate the socio-economic uncertainty (Edenhofer et al., 2010) or use the models' default baseline (Kriegler et al., 2014a). To the knowledge of the authors, this study is the first one discussing optimal climate policy and policy cost measures under uncertainty about the socio-economic baseline.

In this paper, we study the role of uncertainty about the baseline in the assessment of the costs associated with a climate policy. That is, we don't consider other important sources of uncertainty such as technological uncertainties, resource availability or fuel price

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uncertainties, or uncertainties in the climate system, but exclusively consider the role of socio-economic baseline uncertainty. We refer to the population and economic growth scenario as a "baseline" against which a policy scenario is evaluated. Two research questions are at the core of our analysis. First, we ask how the optimal climate policy is affected in the presence of socio-economic uncertainty. Notably, we estimate the cost of socio-economic uncertainty and we compare different decision rules. Second, we discuss how climate change damage costs as well as mitigation policy costs can be measured and compared when the decision maker faces uncertainty about the baseline. Comparing these values across different baseline projections is not trivial, as the costs are typically expressed in relative terms to GDP or consumption of the baseline. We compare different metrics and show how they allow comparisons for different baseline assumptions.

This paper is organised as follows: Section 2 describes the baseline scenarios we use and how we use them to create our socio-economic uncertainty range. Section 3 presents the decision model we use to derive the optimal climate policy for each scenario. Then we present the decision rules: firstly for a known scenario, and then under socio-economic uncertainty, extending existing approaches to take into account uncertain GDP and population projections in Sections 4 and 5. In Section 6 we describe how to define compute, and compare policy costs across different baselines. Section 7 concludes.

2. Socio-economic uncertainty

In order to implement the concept of socio-economic uncertainty, we make use of a set of socio-economic projections that have been recently developed combining the latest available knowledge on demography and economic modelling of long-run dynamics, known as the Shared Socio-economic Pathways (SSPs) (Kriegler et al., 2012; Moss et al., 2010; O'Neill et al., 2015). The SSP scenarios are narratives describing five rather different "futures" in terms of global and regional developments of technological progress, markets, convergence, and population dynamics. The SSPs provide consistent future scenarios including variants of low economic and population growth, different income inequality dynamics, and high growth and divergence in terms of population and economic growth. Rozenberg et al. (2013) performed a scenario elicitation using many drivers to span the socio-economic futures space. In this study, we rather use two main socio-economic drivers, the population and the GDP and we use the projections, associated with the narratives, as they have been implemented and quantified by the International Institute of Applied Systems Analysis (IIASA) (Kc and Lutz, 2014) for population and by the OECD for GDP (Crespo Cuaresma, 2015; Dellink et al., 2015).

The scenarios for the SSPs are labelled SSP1 to SSP5. They include a "Sustainability" scenario (SSP1), a scenario characterized by sustained inequality (SSP4), one based on fossil-fuels development (SSP5), and a scenario of regional rivalry (SSP3). The scenario SSP2 is considered to be a "middle of the road" scenario where the future follows relatively closely historical trends in social, economic, and technological developments (O'Neill et al., 2015). While regional development patterns vary significantly across the five SSPs, we focus on the global picture, as our interest is more conceptually motivated and we are more interested in the globally optimal climate policy. The wide range of the socio-economic developments does however require the creation of a "continuum" of future scenarios, which we will use for the uncertainty analysis in this paper. Here, we construct regional population and GDP time series through a convex combination of the four SSPs, excluding the "middle of the road" scenario SSP2. We perform a Bayesian bootstrap of the four SSPs: we draw random samples from a Dirichlet distribution of order 4 to derive four weights (α_1, α_3, α_4, α_5) associated to the four SSPs requiring that their sum is 1 ($\alpha_1+\alpha_3+\alpha_4+\alpha_5=1$). In total, we obtain 50 trajectories of GDP and population, which we denote by the pair $\{Y,L\}$.

These paths describe the evolution of GDP and population over the 21st century (2005–2100) at the country level (see Fig. 1 for the globally aggregated values). The total variation spans a significant range both in terms of global population (between 7 and 15 billion people in 2100) and per-capita GDP (between 12′000 and 90′000 $\$_{2005}$ in 2100). By construction, all trajectories lie between the lowest (SSP3 for GDP and SSP1 for population) and the highest (SSP5 for GDP and SSP3 for population) projections. The right part of Fig. 1 shows the sample together with its mean and the assumptions of the "middle of the road" scenario SSP2. As expected, both GDP and population projections are very close between the SSP2 and the mean values of our sampled scenarios.

3. The modelling approach

3.1. Computing the optimal consumption profile using an IAM

Based on the socio-economic baseline in terms of total productivity growth (based on the GDP projection) and population, the streams of per-capita consumption $c_{t,r}$ at time t and region r are computed using the WITCH model, which is an integrated assessment model (IAM) describing the world economy in thirteen regions[1] with a detailed representation of the energy sector (Bosetti et al., 2006). WITCH is formulated as a non-linear optimisation problem written in GAMS and solved by the CONOPT solver. The model is solved by maximising global discounted welfare using Negishi weights $w_{t,r}$ as defined in (Nordhaus and Yang, 1996). The time-horizon of the model is 2010–2150.

Population $l_{t,r}$ is an input of the WITCH model whereas GDP is endogenous in the model. Its main driver however is the assumption about growth of total factor productivity. The model is thus calibrated to match the projected baseline GDP per-capita growth rates, so that GDP can be considered as an input to the model, even though technically it is total factor productivity. We calibrate WITCH for each member of the baseline sample described in the previous section.

In this paper, a climate policy is characterised by a carbon budget expressed in gigatons of CO_2 equivalents ($GtCO_2$). The carbon budget, defined as the cumulative global greenhouse gases emissions from 2010 until 2100, is a robust indicator of the expected global warming (Matthews et al., 2009). By solving the mathematical optimisation program (1), the IAM computes all relevant variables, namely investment, investment in energy technologies and other abatement strategies, along with the consumption for a given carbon budget CB.

$$\begin{aligned} \max \quad & \sum_{t,r} w_{t,r} l_{t,r} \frac{(c_{t,r})^{1-\eta}}{1-\eta} \frac{1}{(1+\delta)^t} \\ \text{s.t.} \quad & \sum_{t,r} emi_{t,r}(c_{t,r}) \le CB \end{aligned} \tag{1}$$

We use a social welfare function as in the default setting of the WITCH model with a utility function to be of the isoelastic type where $IES=\eta^{-1}$ denotes the inter-temporal elasticity of substitution, see equation (1). Moreover we consider the default parameter values of $\eta=1.5$ and a pure rate of time preference of $\delta=1\%$.

In order to compute the effects of different climate policy

[1] That is, we aggregate the country-level SSP data to 13 broad world regions.

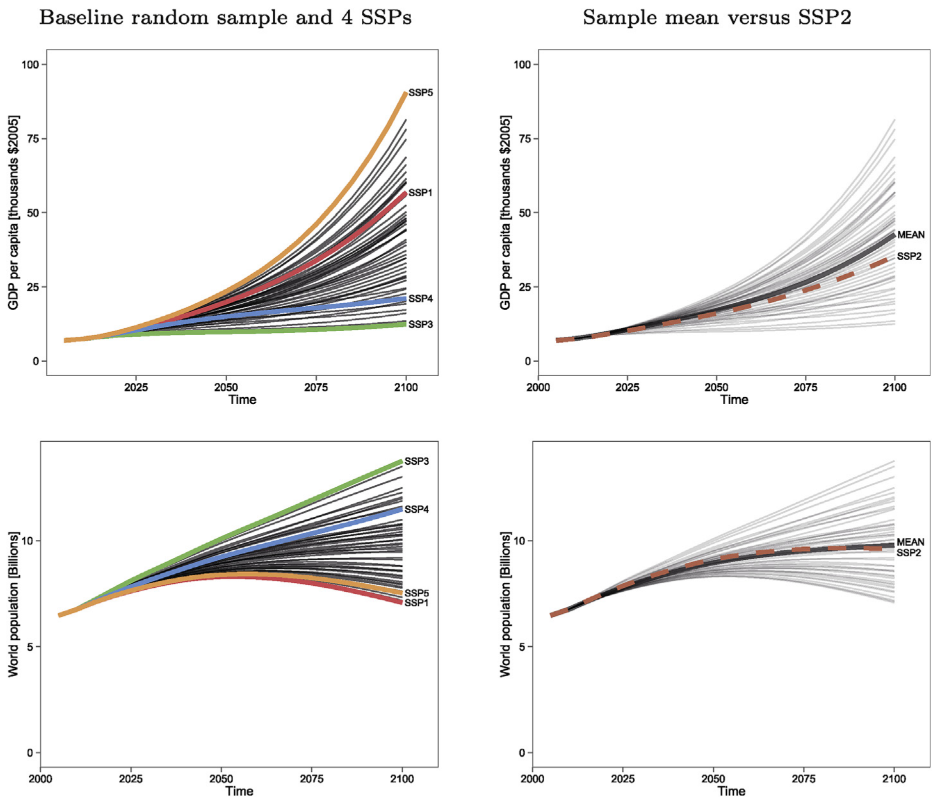


Fig. 1. Baseline projections of the world GDP per capita and the world population from the random sample (in grey) and comparison with the SSP assumptions (coloured). Left hand-side column, comparison with the four SSPs used to build the baseline random sample. Right hand-side, comparison of the sample mean with SSP2. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

targets, we use a sampling method of carbon budgets, similarly as for the baseline. We draw a random sample of the carbon budget *CB* between 500 $GtCO_2$ and 7000 $GtCO_2$ and run the model for each baseline with 100 different carbon budgets, spanning a wide range of future climate change scenarios in terms of global temperature increase. We thus obtain a sequence $c_{t,r}(CB;Y,L)$, namely the consumption profile for a given carbon budget *CB* and a given baseline $\{Y,L\}$, as well as the corresponding greenhouse gas emissions trajectory $emi_{t,r}$.

3.2. Computing the impacts from climate change

The resulting emissions $emi_{t,r}$ as computed by WITCH are fed into a simple climate model, namely a version of the SNEASY model (Urban and Keller, 2010), to compute the global mean temperature increase and other climate variables. Based on the resulting climate, we then compute the regional impacts or damages $d_{t,r}$ using the damage function approach of WITCH. Impacts from climate change include economic impacts of climate change due to sea-level rise, increased energy demand, and agricultural productivity impacts. Moreover, non-market damages including ecosystem losses, non-market health impacts, and catastrophic damages are taken into account. The estimated regional impacts are computed with a damage function depending on global mean temperature *T* as

$$\Omega_{t,r}(T) = 1 + a_{1,r}T + a_{2,r}T^{a_{3,r}}, \tag{2}$$

where the impact factor $\Omega_{t,r}(T)$ is applied multiplicatively to the consumption profile over time and regions. That is, we can write the impacts in per-capita terms $d_{t,r}$ as $d_{t,r} = c_{t,r}(1 - 1/\Omega_{t,r}(T))$. Fig. 2 shows the regional impacts, expressed as relative consumption loss

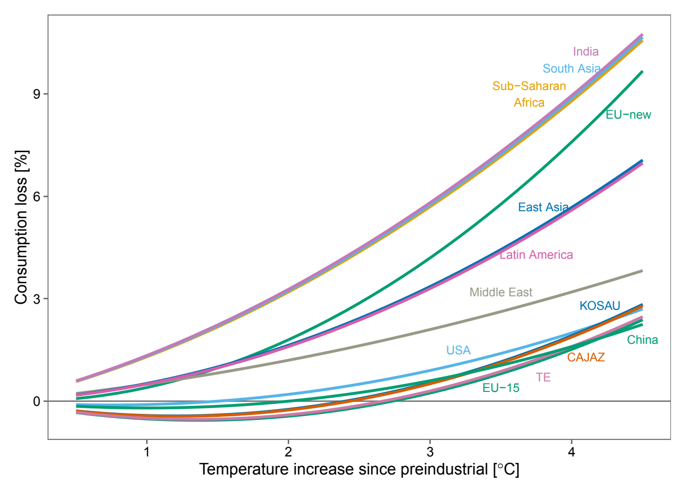


Fig. 2. Region damage functions, expressed as relative consumption loss. CAJAZ: Canada, Japan and New Zealand, KOSAU: South Korea and Australia, TE: transition economies.

$(1 - 1/\Omega_{t,r}(T))$ as a function of the temperature increase.

Finally, we obtain $d_{t,r}(CB;Y,L)$, that is, the damages for a given carbon budget and a given baseline, expressed as per-capita consumption loss. Note that based on this damage function, for temperature increases below three degrees, some regions are expected to experience benefits from global warming. Overall, impacts are below five per cent of consumption, apart from the most vulnerable regions including India, South Asia, and Sub-Saharan Africa.

3.3. Decision framework

Based on the different socio-economic baselines, the different carbon budgets used, and the resulting climate impacts, we now describe the decision theory framework we use in order to determine the optimal climate policy. As presented above, we obtain a stream of per-capita consumption $c(CB;Y,L)t,r$ for any carbon budget considered as well as per-capita climate change impacts or damages $d_{t,r}(CB;Y,L)$. Moreover, we need the population series L over time and across regions for each baseline ($l_{t,r}$). In the following, for the sake of simplicity, we drop the regional index as we focus on the globally aggregated values summed over the thirteen regions of the WITCH model.[2]

The social planner is characterised by the utility function of a representative agent depending on per-capita consumption net of climate impacts $U(c_t - d_t)$, and she evaluates welfare according to the discounted expected utility paradigm. The social planner needs to take the decision on the climate policy today, that is, the expectation $\mathbf{E}_0$ operator is taken with respect to the information available at time zero. This implies that the policy is decided today and the climate policy for the full time horizon is implemented and followed thereafter. This means that we exclude the possibility of learning about the realisation of population and GDP growth. While the effect of learning on the optimal climate policy has been studied in many occasions (Ulph and Ulph, 1997), it is less clear how a process of information acquisition with respect to growth drivers or population projections should be interpreted as compared to e.g., realisations of geophysical model parameters such as the climate sensitivity or the likelihood of catastrophic events.

We assume that the social planner has to decide today on a climate policy represented through a one-dimensional decision variable, namely the carbon budget CB, and that the planner wants to evaluate the costs and benefits from such a policy by calculating the welfare of a resulting pathway of baseline consumption c_t, and associated climate change impacts d_t. For each carbon budget, a different level of mitigation is required to meet the target and hence the baseline consumption c_t is in general decreasing in the stringency of the carbon budget. On the other hand, impacts are typically decreasing as more stringent targets are chosen, so that overall the utility at each point in time specified as $U(c_t - d_t)$ varies across the carbon budgets considered. We can write the social welfare function $W(CB;Y,L)$ for a given socio-economic baseline $\{Y,L\}$ and a specific carbon budget CB as discounted sum of utilities as:

$$W(CB;Y,L) = \sum_{t=0}^{T} l_t U(c_t - d_t) \frac{1}{(1+\delta)^t}. \tag{3}$$

For the utility function we use the isoelastic Constant Relative Risk Aversion (CRRA) function given by $U(c) = \frac{c^{1-\eta}}{1-\eta}$ consistent with the utility function of the WITCH model runs. The social welfare function given in (3) is the main point of analysis and is used throughout this paper.

4. Optimal climate policy for a certain baseline

In the case where the baseline is deterministic, the problem of the social planner consists in maximizing welfare with respect to the carbon budget which yields the optimal carbon budget value $CB^*_{DET}(Y,L)$ for given values of Y and L:

$$\forall \{Y,L\} : CB^*_{DET}(Y,L) = \underset{CB}{\operatorname{argmax}}\ W(CB;Y,L). \tag{4}$$

For each socio-economic baseline, the programme (4) finds the optimal carbon budget according to $\{Y,L\}$.

Fig. 3 shows the obtained welfare function over the space of carbon budget values for one illustrative baseline of the 50 socio-economic scenarios. We can approximate the function $W(CB;Y,L)$ from the 5000-run sample and find the optimal carbon budgets as the one maximizing welfare for each baseline. The approximation is performed using a local polynomial regression fitting as shown in Fig. 3. This way we can compute the optimal climate policy represented by CB^*_{DET} for each baseline scenario given by the GDP and population projection $\{Y,L\}$. The reason for using a decomposed approach to solve the problem (1) is threefold: it allows us to solve the deterministic problems and, later, the problems with uncertain baselines in a consistent way. Secondly, it allows to separate the inter-temporal optimization program from the optimal climate policy target. Finally, it is much less costly in numerical terms while the problems including uncertainty would be intractable using a monolithic formulation.

Fig. 4 shows the set of deterministic optimal climate policies and one can observe that the optimal climate policy is not independent of the baseline. The optimal carbon budget varies substantially ranging from 2500 to 4500 $GtCO_2$ across baseline scenarios. Moreover, welfare tends to be higher for scenarios that find a larger carbon budget optimal, due to the higher overall population and GDP growth in these scenarios. These findings show that the choice of the socio-economic baseline is important for the recommended optimal climate policy.

5. Optimal climate policy under socio-economic uncertainty

Now we move to the main question of this paper, namely the optimal climate policy facing an uncertain socio-economic baseline. To distinguish notation from the previous section, we use the tilde for uncertain variables, which in our case are the baselines given by the pair of GDP and population $\{\tilde{Y},\tilde{L}\}$. Since no probabilities are assigned to the scenarios, we assume a uniform distribution about all the socio-economic scenarios generated. Following from the results of section two, we can infer that the distributions of GDP and population resemble single peaked distributions around the middle of the road scenario of the SSP2, see Fig. 5. This

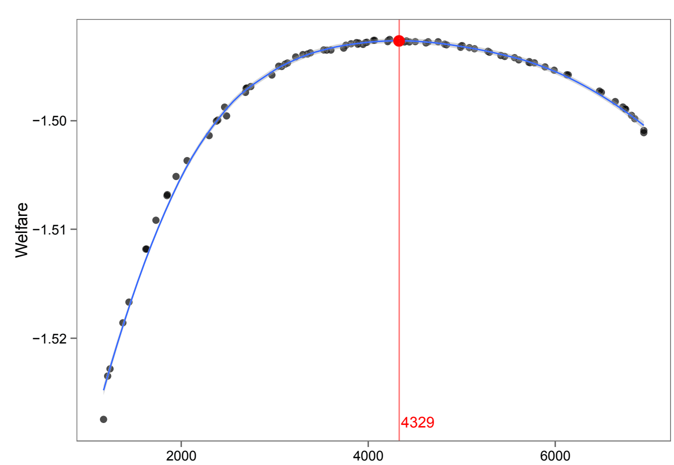


Fig. 3. Illustration of the welfare function approximation and the determination of the optimal carbon budget in the deterministic case. Example for the sampled baseline with $(\alpha_1,\alpha_3,\alpha_4,\alpha_5) = (0,0,1/9,8/9)$.

[2] In the actual computations we use the regionally aggregated data. Since most of the results don't depend on the regional aggregation used, we only refer to it where necessary.

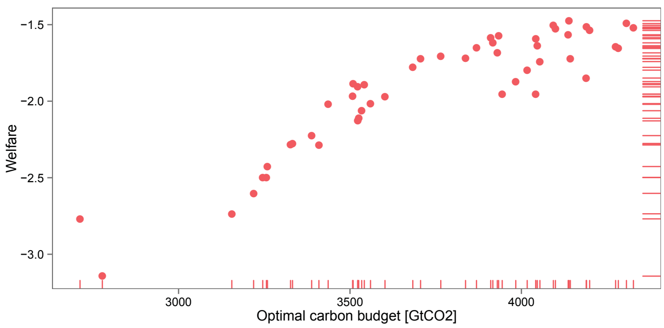


Fig. 4. Distribution of the deterministic optimal carbon budgets and their associated welfare using the baseline sample.

seems to provide a reasonable estimation of the uncertainty around population and GDP growth projections.

As outlined in the introduction, given the socio-economic uncertainty, choosing the optimal climate policy is not obvious as compared to e.g., an uncertain climate sensitivity since the baseline to which climate impacts and mitigation costs are compared to are themselves uncertain. As a starting point, standard expected utility (EU) theory would suggest modifying the program (4) by introducing the expectation operator E_0 taken over the baselines $\{\tilde{Y},\tilde{L}\}$. Given that no learning occurs in our framework, this takes into account all uncertainty present in the model, that is, we can write the optimal carbon budget under uncertainty CB^*_{EU} as:

$$CB^*_{EU} = \underset{CB}{\operatorname{argmax}}\ \ E_0 W\left(CB;\tilde{Y},\tilde{L}\right). \tag{5}$$

Moreover, we can compare the right hand side of (5) evaluated at the optimal value CB^*_{EU} with the expected welfare where the decision is taken optimally for each realisation computed as $E_0 W(CB^*_{DET}(\tilde{Y},\tilde{L});\tilde{Y},\tilde{L})$. The difference in welfare between both decision rules gives the "cost" of the uncertainty or the expected value of perfect information (EVPI) adapted from (Bistline and Weyant, 2013) as:

$$EV\,PI = E_0 W\left(CB^*_{DET}\left(\tilde{Y},\tilde{L}\right);\tilde{Y},\tilde{L}\right) - E_0 W\left(CB^*_{EU};\tilde{Y},\tilde{L}\right).$$

This non-negative value can be interpreted as the welfare loss due to the uncertainty about the baseline compared to a situation where all uncertainty is resolved before taking the decision about the optimal climate policy.

So far, risk aversion by the social planner is captured by the degree of concavity of the utility function $U(c)$. That is, for a typical specification in IAMs such as in WITCH with a parameter value for $\eta = 1.5$, this implies a relatively low value of relative risk aversion compared to empirical estimates (Atkinson et al., 2009), or estimations based on revealed preferences e.g., on financial markets (Epstein and Zin, 1991). Therefore, extensions to the general expected utility framework have been proposed in order to allow for different degrees of risk aversion. In particular, since U also determines inter-temporal preferences, disentangling the two dimensions has been found important in this context. Such generalisations have been proposed in the spirit of (Epstein and Zin, 1989) separating inter-temporal substitution and risk preferences. Given that our framework from a decision theoretic point of view can be considered a single period model, this is equivalent to the framework of Kihlstrom-Mirman (Kihlstrom and Mirman, 1974) preferences (see (Bommier, 2007)). In either case, a concave transformation of the welfare function is introduced. Here, we denote by $f(\cdot)$ a function that is applied to welfare across states of the world. Therefore, if f is concave, this implies a higher degree of risk aversion than if f were linear. Similar to (Berger et al., 2016) and in the spirit of Epstein-Zin (Epstein and Zin, 1989), we write $f = V\circ U^{-1}$ thus decomposing it into the function V and U^{-1}. This approach has the advantage that we can control risk preferences independently by varying V and its measure of concavity captures risk aversion fully, whereas—as before—the function U characterises inter-temporal preferences. Now we can write the decision problem again based on the welfare function (3) with such disentangled preferences as:

$$CB^*_{DIS} = \underset{CB}{\operatorname{argmax}}\ E_0 V\circ U^{-1}\left(W\left(CB;\tilde{Y},\tilde{L}\right)\right), \tag{6}$$

which for the constant relative risk aversion (CRRA) specification with $V(x) = (1-\rho)^{-1}x^{1-\rho}$ implies that

$$CB^*_{DIS} = \underset{CB}{\operatorname{argmax}}\ E_0 \frac{1}{1-\rho}\left(\left\{(1-\eta)W\left(CB;\tilde{Y},\tilde{L}\right)\right\}^{\frac{1-\rho}{1-\eta}}\right). \tag{7}$$

Now we can compute the optimal carbon budget in the presence of baseline uncertainty. Fig. 6 shows these values including the expected utility case (where the violet doted lines cross) and for different degrees of risk aversion maintaining inter-temporal preferences. One observes that baseline uncertainty asks for a lower carbon budget implying a higher level of abatement. Moreover, the effect is non-linear in the degree of risk aversion and high degrees of risk aversion (greater than five) lead to an additional reduction in cumulative emissions of about 600 $GtCO_2$. This additional mitigation effort translates to a reduction in the expected temperature rise by about 0.35 °C in 2100. Fig. 7 summarises the results about the optimal carbon budgets for the different decision rules.

6. Policy cost measures

Besides computing optimal policies, it is also useful to quantify the costs of a climate policy, or of climate impacts using an aggregated measure, see (Paltsev and Capros, 2013) for an overview. Such policy cost measures are computed comparing GDP or

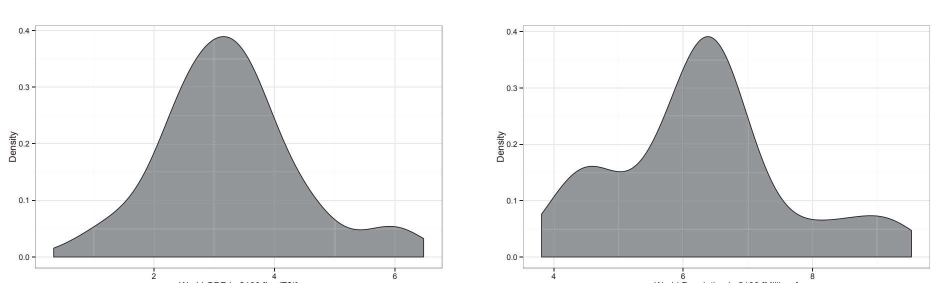
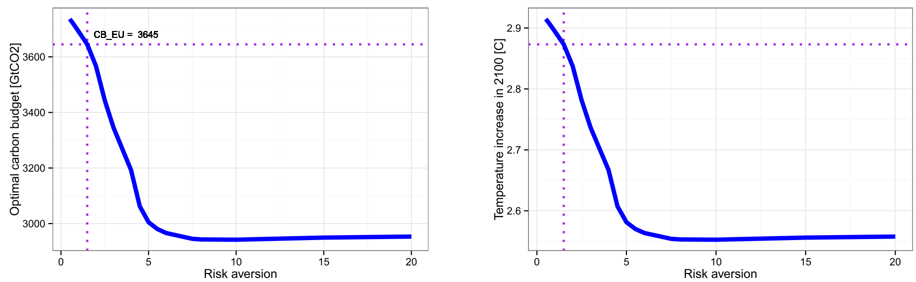


Fig. 5. Marginal distributions of the logarithm of global GDP and the world population in 2100, for the sample baseline and the range of carbon budgets.



(a) Optimal carbon budget (b) Expected temperature increase in 2100

Fig. 6. The optimal carbon budgets under uncertainty and corresponding temperature increases in 2100 for different values of relative risk aversion (ρ).

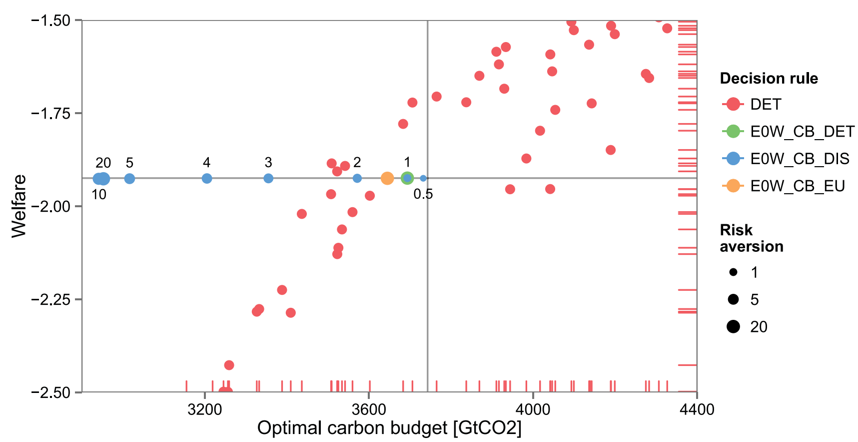


Fig. 7. Comparison of the optimal carbon budgets and their welfare with known baseline (DET), in red, and with an uncertain baseline (E0W). E0W_CB_DET refers to CB^*_{DET}, E0W_CB_EU to CB^*_{EU} and E0W_CB_DIS to CB^*_{DIS}, where the size of the point scales with the degree of relative risk aversion. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

consumption of a scenario with a given policy to the baseline, i.e., the business as usual (bau) scenario run without any policy. Moreover, these measures are typically computed as relative differences. The aggregation of these differences across regions, time, and possibly considering uncertainty requires some assumptions about how to arrive at an aggregate policy cost estimate. The aggregation is typically done by computing the net present value differences in aggregate consumption (or GDP) using a given discount rate r, e.g., $r = 3\%$ or $r = 5\%$, see e.g. (Kriegler et al., 2014b). Alternatively, undiscounted sums of consumption differences have been used to compute the cost of a given policy, that is, setting.$r = 0\%$[3] In general, the formula for the policy cost (PC) of a certain climate policy[4] comparing total consumption[5] between both scenarios is given as:

$$PC = \mathbf{E}_0 \frac{\sum_{t=0}^{T} l_t \left(c_t^{pol} - c_t^{bau} \right) \frac{1}{(1+r)^t}}{\sum_{t=0}^{T} l_t c_t^{bau} \frac{1}{(1+r)^t}}, \tag{8}$$

where the vectors c_t^{pol} and c_t^{bau} refer to the per-capita consumption streams in the policy (pol) and business-as-usual (bau) scenario, respectively.[6] The disadvantage of all those measures is that while easily accessible and intuitive, they lack a foundation in welfare-economic terms. In other words, they do not reflect social preferences of the social planner towards timing, inequality aversion or risk and moreover require the assumption of a discount rate. Moreover, if one wants to compare policy costs for different socio-economic baselines, it is not evident whether such values can be compared due to changed baseline consumption and GDP assumptions. We therefore propose to use an additional measure based on a concept more related to the underlying welfare concept of the economic modelling.

The idea of policy cost measures is deriving an aggregated measure of differences in economic terms reflecting the economic or welfare costs of a climate policy target, or similarly from impacts from climate change, and comparing it to the business as usual scenario. We start by the aggregation over time, making use of the concept of the "balanced growth equivalent" of consumption, which refers to the level of consumption today,[7] that, assuming it grows at a constant growth rate g, would yield the same level of welfare as the actual consumption path. This concept goes back to (Mirrlees and Stern, 1972) and has since been extended to account

[3] For instance used in (Clarke et al.,2008) or the testimony of Bjoern Lomborg before the U.S. Senate, July 29, 2014, available at http://www.epw.senate.gov/public/_cache/files/82dbfab3-bd9b-4a89-8fd3-9f66e9b72398/72914hear-ingwitnesstestimonylomborg.pdf.

[4] Note that the same metric can also be used to compare consumption with and without climate impacts, where the policy cost measure rather provides a measure of climate impacts.

[5] In the following we will always refer to consumption values, but GDP has also been used as economic measure.

[6] Note that this measure is expressed relative to the business-as-usual level of consumption. Absolute policy costs in monetary terms such as the total cost over the time horizon T: $\sum_{t=0}^{T} l_t (c_t^{pol} - c_t^{bau})$ have been reported, but given the long time horizon are much harder to interpret in an intuitive way.

[7] In our case the year 2010.

for uncertainty and inequality across regions as the "certainty, equity, and balanced growth equivalent" (CEBGE), used, e.g., in (Anthoff and Tol, 2009) or (Schmidt et al., 2012) in the context of climate change. Altogether, the CEBGE measures the level of today's consumption that, assuming it were equal across all regions and in all states of the world and growing at a constant[8] growth rate g, would yield the same level of social welfare as the actual consumption pathways across regions and states of the world.

Based on the expected welfare of the scenario runs based on Equation (3) and denoted by $\mathbf{E}_0 W^{\{pol,bau\}}$, we can derive the formula for the CEBGE. Given that under baseline-uncertainty the population varies across states of the world, we have to adapt the definition of the *CEBGE* for the different population projections,[9] and we obtain for our utility specification with the CRRA utility that

$$CEBGE = \left[\frac{\mathbf{E}_0 W(1-\eta)}{\sum_{t=0}^{T} \mathbf{E}_0 l_t \frac{(1+g)^{(1-\eta)t}}{(1+\delta)^t} dt} \right]^{\frac{1}{1-\eta}}. \qquad (9)$$

That is, only the expected welfare W obtained from Equation (3), the population size, and the assumed growth rate g are required for the computation of the *CEBGE*.[10]

It therefore provides a measure in monetary terms of the social welfare of each scenario. Notably, this formula holds for all the welfare specifications used above since the *CEBGE* is equal across regions and states of the world and therefore independent of inequality and risk preferences. Based on this measure, we can now derive our policy cost measure, which we denote as $\Delta CEBGE$. It is obtained by simply computing the *relative* difference between the *CEBGE* of a climate policy run and the corresponding business as usual (bau) scenario run[11]:

$$\Delta CEBGE \equiv \frac{CEBGE^{pol} - CEBGE^{bau}}{CEBGE^{bau}} = \left(\frac{\mathbf{E}_0 W^{pol}}{\mathbf{E}_0 W^{bau}} \right)^{\frac{1}{1-\eta}} - 1. \qquad (10)$$

This measure turns out to be relatively simple to compute. Notably, it does not anymore depend on the assumed constant growth rate g. Therefore, it allows the comparison of the economic welfare of two scenario runs or policies directly in a straightforward and easy-to-interpret way. We now can compare this measure to the typically used policy cost measures. It is easy to show that the two measures coincide if $\eta = \rho = 0$ and moreover the discount rate for computing the policy cost is equal to the pure rate of time preference ($r = \delta$), in which case we always have that $\Delta CEBGE = PC$. Intuitively, this measure removes the regional and inter-temporal patterns of consumption between different scenarios. While it is a relative measure as a set of policy and baseline scenarios are compared, the comparison is reduced to a comparison of two scalars. Moreover, it has the traditional PC measure as a special case.[12]

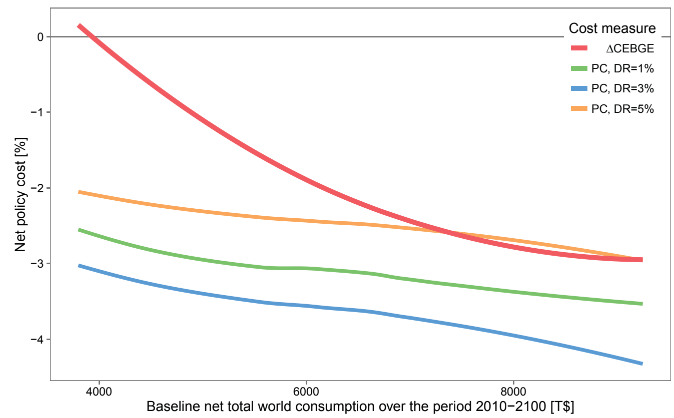


Fig. 8. Comparison of the policy cost measures compatible with a 2 °C target in 2100 across baseline as functions of the baseline total consumption over the 21st century.

In order to compare the different measures in an application, we compare the traditional policy cost measures with the CEBGE based on a climate policy aiming at stabilising global warming at two degrees.[13] We compute the different cost measures for all baseline GDP and population scenarios used for the carbon budget compatible with a 2 °C target in 2100 (Fig. 8). The results show that the policy costs according to the PC measure are slightly increasing (in absolute terms) in total consumption in the baseline. The reason of this increase in costs is that at higher GDP and thus energy demand, mitigation becomes increasingly costly at least to some extent. Interestingly, the policy costs are not monotonic in the discount rate r used. In particular, using a medium value of 3% leads to the highest policy costs. The reason is that due to the very different inter-temporal dynamics of (earlier) mitigation costs and (later) climate change impacts, it is not clear how the inter-temporal aggregation leads to higher or lower aggregated policy costs for different discount rates. When using the $\Delta CEBGE$ measure on the other hand, no discount rate assumption is needed. The increase in the policy cost measure now becomes even more pronounced. For baselines with a low projected total GDP, on the other hand, the net policy costs are much lower and at some point even positive since welfare is higher under the two degree policy due to much reduced damages and, at this level of overall economic growth, comparably low mitigation costs. These results show the sensitivity of policy cost measures to the baseline.

Now we turn to the full set of runs based on different baselines and carbon budgets and compute the expected policy cost measures for each carbon budget. These measures of total climate policy costs are displayed in Fig. 9 for all model runs compared to the respective business as usual scenario including impacts.[14]

We observe that for very low carbon budgets all measures indicate a very high policy cost due to the high mitigation costs in these scenarios. For high carbon budgets and hence emissions, impacts from climate change increase while mitigation costs are reduced while the latter effect dominates. Notably, the CEBGE seems to provide a more balanced welfare based evaluation of

[8] In the numerical application, we set this growth rate to 1.5% reflecting the long-term average of projected GDP growth.

[9] In the previous literature, the population was has always been considered the same across different future states of the world, which is not the case in our situation. Therefore, we obtain a modified version which includes the expected population in the definition of the *CEBGE*.

[10] Given that we use a regionally disaggregated model, the actual implemented formula includes the aggregation over regions. Since Negishi weights are used in the optimization, marginal welfare of consumption is equalized across regions so that the CEBGE is not different from a global model with the average per capita consumption level.

[11] Note that in the CBA framework of this paper, we include also impacts in the bau scenario, which is the reasonable point of comparison for a climate policy consideration.

[12] Note that even if the Ramsey consumption discount rate were to be used in the computation of (8), the two measures do not coincide since the CEBGE takes into account the distribution not only over time, but also across regions, and states of the world (uncertainty). We thank an anonymous referee for pointing this out.

[13] According to the IPCC WGI AR5 (Stocker et al., 2013), cumulative CO_2 emissions over the 21st century of between 1200 and 1300 $GtCO_2$ are compatible with a two degree Celsius temperature increase in 2100.

[14] The expected policy cost measures are computed for different carbon budgets using a smoothed Generalized Additive Model (GAM).

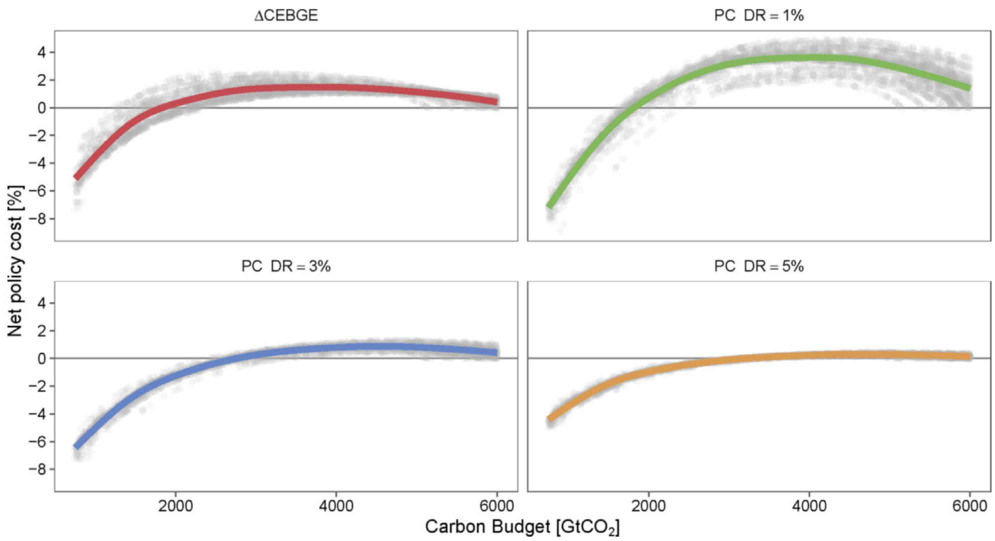


Fig. 9. Comparison of the policy cost measures combining impacts and mitigation costs for all carbon budgets. The colored lines show the averaged policy costs across baselines. The grey points show the policy cost for each individual runs, depicting the surrounding uncertainty imputable to the baseline.

Table 1
Expected policy cost measures for given decision criterion. NOCC refers to the case of no climate change impact and no climate policy.

	Decision criterion			
	NOCC	$CB^*_{DET}(\tilde{Y},\tilde{L})$	CB^*_{EU}	CB^*_{DIS}, $\rho = 20$
Carbon budget [$GtCO_2$]		2500–4500	3645	2953
CEBGE[$]	2367.3$	2454.3$	2453.1$	2450.1$
$\Delta CEBGE$		3.68%	3.63%	3.50%
$PC_{r=1\%}$		3.60%	3.59%	3.08%
$PC_{r=3\%}$		0.68%	0.66%	0.21%
$PC_{r=5\%}$		0.16%	0.14%	−0.13%

mitigation costs and damages, showing a flatter profile in general but increasing costs towards both extremes. One can also note that the policy cost measures depend crucially on the discount rate chosen, since for lower discount rates, impacts happening farther in the future have a much higher weight leading to a steeper decrease at high carbon budget values.

While these measures allow an intuitive comparison of different climate policy targets, the optimal climate policy can be computed using the optimal decision rules of the previous section. Based on the results under different decision rules, we compute the different expected policy cost measures, which we report in Table 1.

The results suggest that in terms of the *CEBGE*, choosing the optimal climate policy leads to a welfare gain of on average 3.7% over the business as usual scenario that includes impacts form climate change. Under baseline uncertainty, this welfare gain is slightly reduced to about 3.5% for a reasonable degree of risk aversion of $\rho = 20$, or by about 5% in relative terms, computed from the table as the EVPI based on the CEBGE as $\frac{0.0350}{0.0368} - 1$. When looking at the traditional policy cost measures, the net policy costs values are also positive, except for the case of a 5% discount rate and the high degree of risk aversion, in which case the high discounting of future impacts leads to a negative welfare impact of the climate policy. The *PC* measures also depend crucially on the discount rate used. Moreover, the effect of uncertainty is significantly larger according to the *PC* measures, whereas the CEBGE provides a more balanced picture. Note that in terms of magnitude, the estimated costs of the socio-economic uncertainty, albeit relatively small in absolute terms ranging from 0.2 to 0.5 percentage points, imply consumption losses throughout the time horizon and across all regions and in all possible realisations of the underlying economic and population growth.

7. Conclusion

In this paper, we analyse the impact of uncertain socio-economic baseline assumptions for the optimal climate policies, and how policy costs can be compared and evaluated if GDP and population growth are subject to uncertainty. Using a range of socio-economic scenarios, we demonstrate how they can be used to span a space of uncertainty and thus provide a distribution of future socio-economic development. We find that the optimal climate policy, characterised by a carbon budget, varies significantly for different baseline scenarios.

Moreover, we show that under uncertainty, the optimal decision leads to a more precautionary policy. Given that policy costs and other measures such as impacts are typically expressed relative to a baseline, comparing those values with differing baseline projections is not trivial. In this context, consumption or GDP losses, in absolute or relative terms, are no longer easily comparable across different baselines or scenarios.

Policy cost measures based on the CEBGE provide a way to combine different baselines making the evaluation of consumption losses comparable. Moreover, this measure avoids the (arbitrary) choice of a discount rate for the computation of the policy cost measure, which has a strong effect due to the very different timing of costs and benefits in the context of climate change. We use different measures of policy costs in our application and show the different implications and how such measures can be compared. The two main methods presented here, scenario uncertainty analysis and policy cost computation based on welfare-based measures, provide tools that can be applied in different modelling contexts to integrate socio-economic baseline uncertainties. For our scenario analysis based on two main baseline drivers of the SSPs, we found that taking into account this baseline uncertainty leads to a moderate increase in the welfare costs of climate change over the costs under a certain socio-economic baseline. It is important to note that we consider only uncertainties in the two baseline drivers but do not incorporate uncertainties about technologies or the climate system, which could lead to different results, notably a potentially much increased scope for a more precautionary optimal climate policy.

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References

Anthoff, D., Tol, R.S.J., 2009. The impact of climate change on the balanced growth equivalent: an application of fund. Environ. Resour. Econ. 43 (3), 351–367. http://dx.doi.org/10.1007/s10640-009-9269-5.

Arent, D., Tol, R., Faust, E., Hella, J., Kumar, S., Strzepek, K., Tóth, F., Yan, D., 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part a: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 659–708. Ch. 10 Key economic sectors and services.

Arrow, K., Cropper, M., Gollier, C., Groom, B., Heal, G., Newell, R., Nordhaus, W., Pindyck, R., Pizer, W., Portney, P., Sterner, T., Tol, R.S.J., Weitzman, M., 2013. Determining benefits and costs for future generations. Science 341 (6144), 349–350. http://dx.doi.org/10.1126/science.1235665.

Atkinson, G.D., Dietz, S., Helgeson, J., Hepburn, C., Sælen, H., 2009. Siblings, not triplets: social preferences for risk, inequality and time in discounting climate change. Econ. Open Access, Open Assess. E-J. 26 (3), 1–29. http://ideas.repec.org/p/zbw/ifwedp/7493.html.

Berger, L., Emmerling, J., Tavoni, M., 2016. Managing catastrophic climate risks under model uncertainty aversion. Manage. Sci. forthcoming.

Bistline, J.E., Weyant, J.P., 2013. Electric sector investments under technological and policy-related uncertainties: a stochastic programming approach. Clim. Change 121 (2), 143–160. http://dx.doi.org/10.1007/s10584-013-0859-4.

Bommier, A., 2007. Risk aversion, intertemporal elasticity of substitution and correlation aversion. Econ. Bull. 29 (4). http://ideas.repec.org/a/ebl/ecbull/v4y2007i29p1-8.html.

Bosetti, V., Carraro, C., Galeotti, M., Massetti, E., Tavoni, M., 2006. WITCH: a world induced technical change hybrid model,. Energy J. 2, 13–38 (hybrid Modeling, Special Issue).

Clarke, L., Kyle, P., Wise, M., Calvin, K., Edmonds, J., Kim, S., Placet, M., Smith, S., 2008. Co_2 Emissions Mitigation and Technological Advance: an Updated Analysis of Advanced Technology Scenarios. PNNL Report Pacific Northwest National Laboratory, Richmond.

Chapman, Hall/CRC (Eds.), Classification and Regression Trees, Leo Breiman, Jerome Friedman, Charles J. Stone, R.A. Olshen, 1984.

Crespo Cuaresma, J., 2015. Income projections for climate change research: a framework based on human capital dynamics. Glob. Environ. Change. online http://dx.doi.org/10.1016/j.gloenvcha.2015.02.012.

Crost, B., Traeger, C.P., 2014. Optimal CO_2 mitigation under damage risk valuation. Nat. Clim. Change 4 (7), 631–636. http://dx.doi.org/10.1038/nclimate2249.

Dellink, R., Chateau, J., Lanzi, E., Magné, B., 2015. Long-term Economic Growth Projections in the Shared Socioeconomic Pathways. Glob. Environ. Change online.

Dietz, S., 2012. The treatment of risk and uncertainty in the US social cost of carbon for regulatory impact analysis, Economics: The Open-Access. Open-Assessment E-Journal 6 (18).

Drouet, L., Bosetti, V., Tavoni, M., July 2015. Selection of climate policies under the uncertainties in the Fifth Assessment Report of the IPCC. Nat. Clim. Change 5, 937–940. http://dx.doi.org/10.1038/nclimate2721.

Edenhofer, O., Knopf, B., Barker, T., Baumstark, L., Bellevrat, E., Chateau, B., Criqui, P., Isaac, M., Kitous, A., Kypreos, S., Leimbach, M., Lessmann, K., Magné, B., Turton, H., van Vuuren, D.P., 2010. The economics of low stabilization: model comparison of mitigation strategies and costs. Energy J. 31 (1), 11–48.

Epstein, L.G., Zin, S.E., 1989. Substitution, risk aversion, and the temporal behavior of consumption and asset returns: a theoretical framework. Econometrica 57 (4), 937–969. http://www.jstor.org/stable/1913778.

Epstein, L.G., Zin, S.E., 1991. Substitution, risk aversion, and the temporal behavior of consumption and asset returns: an empirical analysis. J. Political Econ. 99 (2), 263–286. http://www.jstor.org/stable/2937681.

Gillingham, K., Nordhaus, W.D., Anthoff, D., Blanford, G., Bosetti, V., Christensen, P., McJeon, H., Reilly, J., Sztorc, P., October 2015. Modeling Uncertainty in Climate Change: a Multi-model Comparison, Working Paper 21637. National Bureau of Economic Research.

Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), 2013. IPCC, Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Kc, S., Lutz, W., 2014. The human core of the shared socioeconomic pathways: population scenarios by age, sex and level of education for all countries to 2100. Glob. Environ. Change. online http://dx.doi.org/10.1016/j.gloenvcha.2014.06.004.

Kihlstrom, R.E., Mirman, L.J., 1974. Risk aversion with many commodities. J. Econ. Theory 8 (3), 361–388. http://dx.doi.org/10.1016/0022-0531(74)90091-X.

Kriegler, E., O'Neill, B.C., Hallegatte, S., Kram, T., Lempert, R.J., Moss, R.H., Wilbanks, T., 2012. The need for and use of socio-economic scenarios for climate change analysis: a new approach based on shared socio-economic pathways. Glob. Environ. Change 22 (4), 807–822. http://dx.doi.org/10.1016/j.gloenvcha.2012.05.005.

Kriegler, E., Weyant, J.P., Blanford, G.J., Krey, V., Clarke, L., Edmonds, J., Fawcett, A., Luderer, G., Riahi, K., Richels, R., Rose, S.K., Tavoni, M., van Vuuren, D.P., 2014. The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies. Clim. Change 123 (3–4), 353–367.

Kriegler, E., Weyant, J.P., Blanford, G.J., Krey, V., Clarke, L., Edmonds, J., Fawcett, A., Luderer, G., Riahi, K., Richels, R., Rose, S.K., Tavoni, M., van Vuuren, D.P., 2014. The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies. Clim. Change 123 (3–4), 353–367. http://dx.doi.org/10.1007/s10584-013-0953-7.

Kunreuther, H., Heal, G., Allen, M., Edenhofer, O., Field, C.B., Yohe, G., 2013. Risk management and climate change. Nat. Clim. Change 3 (5), 447–450.

Lempert, R.J., Popper, S.W., Bankes, S.C., 2003. Shaping the Next One Hundred Years: New Methods for Quantitative, Long-term Policy Analysis. RAND Corporation, Santa Monica, CA.

Lontzek, T.S., Cai, Y., Judd, K.L., Lenton, T.M., 2015. Stochastic integrated assessment of climate tipping points indicates the need for strict climate policy. Nat. Clim. Change 5 (5), 441–444. http://dx.doi.org/10.1038/nclimate2570.

Matthews, H.D., Gillett, N.P., Stott, P.A., Zickfeld, K., 2009. The proportionality of global warming to cumulative carbon emissions. Nature 459 (7248), 829–832. http://dx.doi.org/10.1038/nature08047.

Millner, A., Dietz, S., Heal, G., 2013. Environ. Resour. Econ. 55 (1), 21–46. http://dx.doi.org/10.1007/s10640-012-9612-0.

Mirrlees, J.A., Stern, N.H., 1972. Fairly good plans. J. Econ. Theory 4 (2), 268–288. http://dx.doi.org/10.1016/0022-0531(72)90153-6.

Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., van Vuuren, D.P., Carter, T.R., Emori, S., Kainuma, M., Kram, T., et al., 2010. The next generation of scenarios for climate change research and assessment. Nature 463 (7282), 747–756.

Nordhaus, W.D., Yang, Z., 1996. A regional dynamic general-equilibrium model of alternative climate-change strategies. Am. Econ. Rev. 86 (4), 741–765. http://dx.doi.org/10.2307/2118303.

O'Neill, B.C., Kriegler, E., Ebi, K.L., Kemp-Benedict, E., Riahi, K., Rothman, D.S., van Ruijven, B.J., van Vuuren, D.P., Birkmann, J., Kok, K., et al., 2015. The roads ahead: narratives for shared socioeconomic pathways describing world futures in the 21st century. Glob. Environ. Change. online http://dx.doi.org/10.1016/j.gloenvcha.2015.01.004.

Paltsev, S., Capros, P., 2013. Cost concepts for climate change. Clim. Change Econ. 04 (Suppl. 01), 1340003. http://dx.doi.org/10.1142/s2010007813400034.

Rogelj, J., Meinshausen, M., Knutti, R., 2012. Global warming under old and new scenarios using IPCC climate sensitivity range estimates. Nat. Clim. Change 4 (2), 248–253. http://dx.doi.org/10.1038/nclimate1385.

Rozenberg, J., Guivarch, C., Lempert, R., Hallegatte, S., 2013. Building SSPs for climate policy analysis: a scenario elicitation methodology to map the space of possible future challenges to mitigation and adaptation. Clim. Change 122 (3), 509–522. http://dx.doi.org/10.1007/s10584-013-0904-3.

Schmidt, M.G.W., Held, H., Kriegler, E., Lorenz, A., 2012. Environ. Resour. Econ. 54 (1), 79–99. http://dx.doi.org/10.1007/s10640-012-9582-2.

Ulph, A., Ulph, D., 1997. Global warming, irreversibility and learning. Econ. J. 107 (442), 636–650. http://www.jstor.org/stable/2957790.

Urban, N.M., Keller, K., 2010. Probabilistic hindcasts and projections of the coupled climate, carbon cycle and Atlantic meridional overturning circulation system: a Bayesian fusion of century-scale observations with a simple model. Tellus A 62 (5), 737–750.

Urban, N.M., Holden, P.B., Edwards, N.R., Sriver, R.L., Keller, K., 2014. Historical and future learning about climate sensitivity. Geophys. Res. Lett. 41, 2543–2552. http://dx.doi.org/10.1002/2014GL059484.

Weitzman, M.L., 2009. On modeling and interpreting the economics of catastrophic climate change. Rev. Econ. Stat. 91 (1), 1–19. http://dx.doi.org/10.1162/rest.91.1.1.