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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.