



Net0Pathways through impRoved IAMs across Sectors, diMensions, and scAles

Deliverable 6.1

Report on uncertainty exploration and robust decision making

(based on task 6.2)

Deliverable 6.1
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Author(s)	Celine Guivarch (ENPC), Laurent Drouet (CMCC), Johannes Emmerling (CMCC), Thomas Le Gallic (ENPC), Xin Wen (UNIGE), Marc Jaxa-Rozen (UNIGE), Nik Zielonka (UNIGE), Evelina Trutnevyte (UNIGE), Laura Diaz Anadon (UCAM), Rupert Way (UCAM), Sergey Kolesnikov (UCAM)
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1. Introduction

Description of Tasks 6.2:

Task 6.2: Uncertainty exploration and robust decision making (Lead: ENPC, Partners: UNIGE, CMCC, UCAM)

The aim of this task is to explore and quantify the uncertainties characterizing model scenarios and to identify emission reduction (and adaptation) strategies which are robust to deep uncertainties. The task will review the thousands of scenarios produced by the community and summarized by the Intergovernmental Panel on Climate Change Sixth Assessment Report (IPCC AR6) Scenario Explorer (which will be publicly available in April 2022) in addition to those produced by this project and analyze the key dimensions of uncertainty not explored so far. It will also link to T3.3 on uncertainty around technological change. Computational (e.g., scenario discovery) and machine learning (e.g. clustering) techniques will be applied to quantify the missing uncertainties and pin down key drivers of model uncertainties for key policy questions identified by stakeholders in WP1. Finally, the scenarios will be fed to social choice models for quantifying the impact of social choices beyond the standard economic ones (e.g., capturing inequality, risk and ambiguity aversion) on policy relevant outcomes such as the timing of emission reductions, the regional distribution of abatement, and the amount of CO₂ removals.

Within task 6.2, the teams have developed a number of studies, seven in total, that are summarized in section 2 for studies exploring uncertainties in models' inputs and scenarios and in section 3 for studies that extend decision making under uncertainty with social choice models that account for risk and ambiguity aversion. The full manuscripts of the studies are given in Annex.

The studies on uncertainty exploration focus on key aspects of uncertainty for mitigation pathways. First, one article shows that demographic uncertainties are insufficiently represented in scenario ensembles that inform IPCC assessment, and details how incorporating probabilistic demographic projection would better capture the existing spread in projections. Then, a second article disentangles the sources of uncertainty for fossil fuels reduction pathways and highlights the criticality of the assumption on carbon dioxide removal (CDR) potential. It finds that the uncertainty in fossil fuels reduction is greatly reduced when potentials of key CDR options (BECCS, biomass energy with carbon capture and sequestration, DACCS, direct air carbon capture and sequestration, and afforestation) are constrained by expert consensus assessments. The third study precisely focuses on DACCS, and provides the first global sensitivity analysis of modelling results to uncertainty on DACCS. The fourth section describes how probabilistic technology cost forecasts, previously developed for key low-carbon and clean energy technologies in task 3.3, can be used in global sensitivity analysis of the models to the uncertainty of future technology costs. Together, the studies on uncertainty exploration demonstrate how state-of-the-art methods to characterize uncertainty - in particular global sensitivity analysis and clustering - can be applied to Integrated Assessment Models for novel insights. The last study applies empirical density forecasting methods to produce probabilities projections for the electricity sector in 31 European countries.

The two studies that use social choice models that capture forms of risk and uncertainty aversion both



suggest more stringent climate targets become optimal when accounting for uncertainty. The first focuses on the risk of tipping points. It shows that social choice that represents temporal risk aversion is particularly relevant in this case, and is quantitatively as important as the value of the discount rate. The second article extends the decision framework to encompass model misspecification. It shows that when confidence in model outputs is low, more stringent mitigation action should be taken.

2. Exploring and quantifying the uncertainties characterizing models' inputs and scenarios

2.1. Underestimating demographic uncertainties in the synthesis process of the IPCC

The paper “Underestimating demographic uncertainties in the synthesis process of the IPCC” co-authored by Sara Giarola, Leonardo Chiani, Laurent Drouet, Giacomo Marangoni, Francesco Nappo, Raya Muttarak and Massimo Tavoni.

This study critically examines how demographic assumptions, in particular population projections, are incorporated into the climate/emissions scenarios assessed by the Intergovernmental Panel on Climate Change (IPCC). Population size, structure, and education levels are central to future greenhouse gas (GHG) emissions, energy demand, and vulnerability to climate change. Despite this importance, the study finds that demographic uncertainty has been insufficiently represented in the scenario ensembles that inform IPCC assessments.

The authors compare the population trajectories embedded in the IPCC databases (AR5, SR1.5, AR6) with authoritative international sources such as the UN, Eurostat, World Bank, and IHME (Figure 1). They identify a systematic undersampling of population uncertainty: most scenarios converge on the “middle-of-the-road” Shared Socioeconomic Pathway (SSP2), neglecting the wider range of plausible demographic futures. This over-reliance on SSP2 reduces the diversity of scenarios considered and risks underestimating vulnerabilities, particularly in regions where fertility, mortality, and migration uncertainties are greatest.



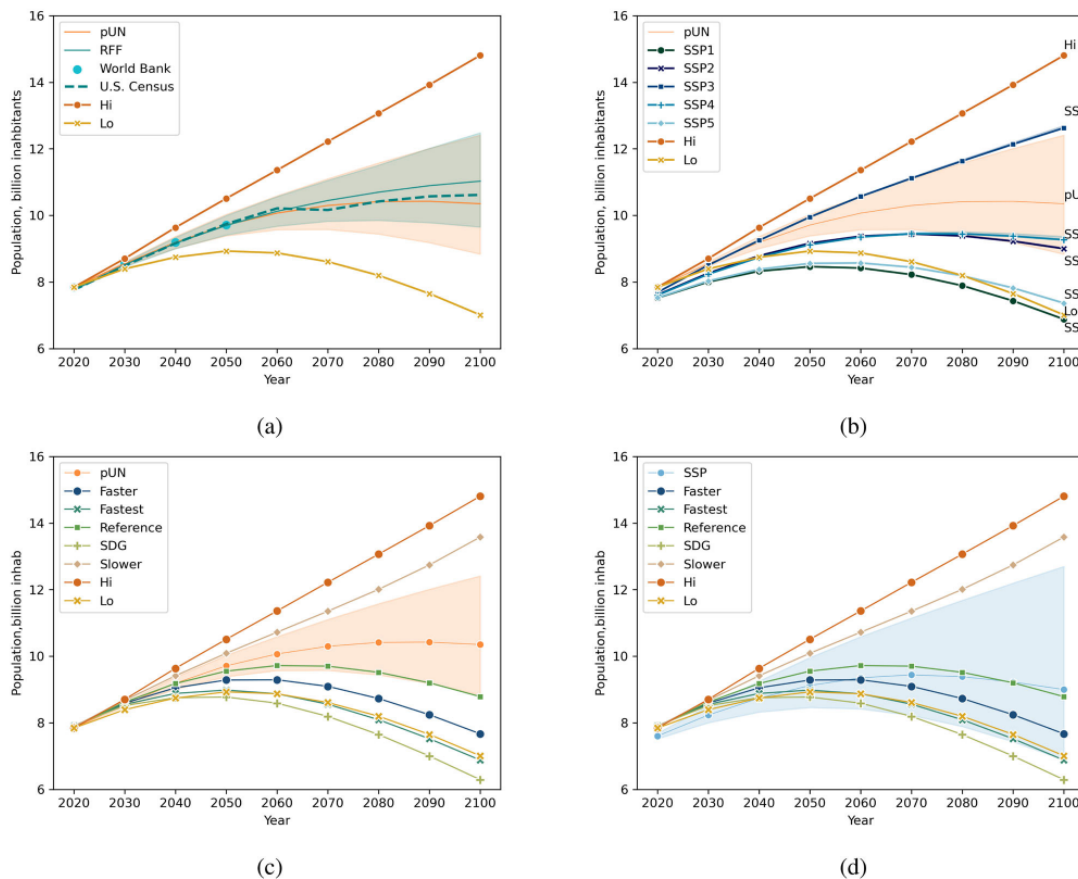


Fig. 1 | Population projections from global databases. Panel (a) shows the global population projections developed by UN, the United Nations, (pUN) (a faded orange area represents the 5th to 95th percentile range and a bold orange line depicts the median²⁵); the U.S. Census projection (International Database), shown with a blue continuous line; the World Bank estimates shown in blue circles; the 5th to 95th percentile range of the probabilistic distribution developed by Resources for the Future (RFF)³² in green; the highest and lowest deterministic scenarios developed by UN (dUN) (the “High variant” and the “Low variant”, named “Hi” and “Lo” scenarios, shown respectively in orange and in gold²⁵). Panel (b) shows the United Nation Population Prospects (pUN)²⁵; the highest and lowest deterministic

scenarios developed by UN (dUN), “Hi” and “Lo”²⁵; and the SSPs, the Shared Socioeconomic Pathways (SSP1, SSP2, SSP3, SSP4, and SSP5) developed by IIASA⁸. Panel (c) overlays the pUN distribution, with the highest and lowest deterministic scenarios developed by UN (dUN) (“Hi” and “Lo”), and the scenarios developed by IHME (Institute for Health Metrics and Evaluation) which projected scenarios of faster or slower achievement of education and Sustainable Development Goals (SDG) (“Faster Met Need and Education” (“Faster”), “Fastest Met Need and Education” (“Fastest”), “Reference”, “SDG Met Need and Education” (“SDG”), “Slower Met Need and Education” (“Slower”)³³). Panel (d) overlays the SSP range, with the “Hi” and “Lo” scenarios, and with the IHME scenarios.

The paper also shows that illustrative pathways in AR6 predominantly rely on SSP2, further narrowing the exploration of population outcomes. Regional and subregional analyses confirm that the lack of demographic spread occurs globally as well as locally, where demographic heterogeneity is crucial for assessing adaptation and risk. The authors argue that incorporating probabilistic and expert-elicited projections (such as UN probabilistic forecasts or IIASA/RFF approaches) would better capture uncertainties and enrich scenario ensembles.

Overall, the study calls for a new methodology to ensure the IPCC synthesis process reflects a broader set of demographic futures. Doing so would improve the robustness of mitigation and adaptation assessments, making them more policy-relevant in a world where demographic dynamics remain deeply uncertain.

2.2. Exploring uncertainty in global fossil-fuel reduction in mitigation pathways

This work has been published as: Achakulwisut, P., Erickson, P., Guivarch, C. et al. Global fossil fuel reduction pathways under different climate mitigation strategies and ambitions. *Nat Commun* 14, 5425 (2023). <https://doi.org/10.1038/s41467-023-41105-z> (see full manuscript in Appendix)

The combustion of fossil fuels is a major contributor to anthropogenic climate change; and the reduction of fossil-fuel extraction and uses is both critical for mitigation and contested in international climate change negotiations. The existing mitigation pathways explore the uncertainty in fossil-fuel reductions compatible with climate goals. In this study, we disentangle the sources of uncertainty in those pathways.

More precisely, we use the mitigation scenarios database of the Intergovernmental Panel on Climate Change's Sixth Assessment Report (AR6) and analyze the scenarios consistent with limiting warming to 2 °C or below regarding the speed, trajectory, and feasibility of different fossil fuel reduction pathways.

We explore the sensitivity of global fossil fuel reduction pathways to uncertainties in Carbon Dioxide Removal (CDR) potential. We retain from the AR6 database the pathways constrained by the potential 2020-2100 cumulative availability of BECCS (196 GtCO₂), afforestation (224 GtCO₂), and DACCS (320 GtCO₂) based on a recent expert consensus survey (Grant et al., 2021). The selected scenarios also have levels of total CCS (coupled to fossil fuel use, bioenergy use, and direct air capture) below 8.6 GtCO₂ per year around mid-century, which is the “investable” CO₂ storage capacity estimated by Grant et al. (2022) after accounting for real-world regional differences in storage capacity and injection rates. Imposing these CDR limits implies much faster and greater reductions in fossil fuel supply and use compared to the full AR6 ensemble, especially for gas, in the near- and long-term. As the Figure 2 below shows, the resulting median coal, oil, and gas reduction pathways fall around or below the 25th percentile of all scenarios. For example, under the median pathway calculated from all C1 scenarios, global coal, oil, and gas supply declined by 95%, 62%, and 42%, respectively, between 2020 and 2050. Under the median pathway of the CDR-limited scenarios, the respective declines are 99%, 70%, and 84%.



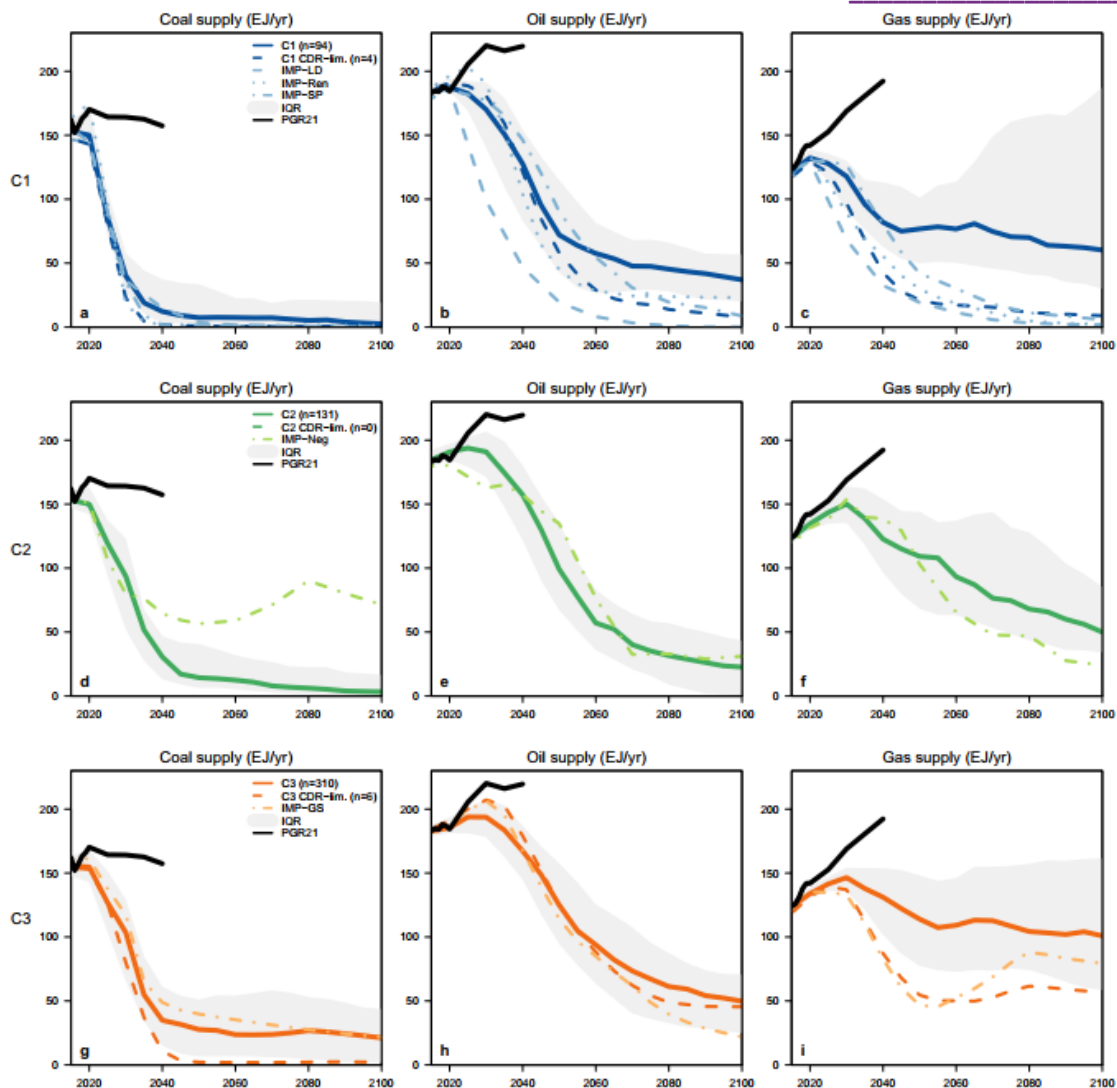


Fig. 5 | 2015–2100 global pathways of fossil fuel supply under different individual or subsets of AR6-assessed scenarios and compared to those based on government plans and projections. Panels a–i show global pathways of primary energy supply (in exajoules, EJ) from coal, oil, and gas under different subsets of or individual C1–C3 pathways as denoted inset: (1) the median pathway (solid lines) and interquartile ranges (IQRs, grey shadings) of all scenarios (“n” denotes the number of scenarios); (2) the median pathway of scenarios constrained by cumulative BECCS, afforestation, and DACCS limits based on expert consensus of their future CDR potential¹⁹ (“CDR-lim.”); and (3) individual AR6 illustrative

mitigation pathways: “IMP-LD” – strong emphasis on energy demand reductions; “IMP-Ren” – heavy reliance on renewables; “IMP-SP” – mitigation in the context of broader sustainable development; “IMP-Neg” – extensive CDR in the energy and the industry sectors; and “IMP-GS” – less rapid and gradual strengthening of near-term mitigation actions. The projected levels of supply based on government plans and projections are shown by the black lines (“PGR21”), as estimated in the 2021 Production Gap Report⁶. See Supplementary Table 1 for the percentage reductions in coal, oil, gas supply relative to 2020 under all pathways shown.

Figure 2. Source: Achakulwisut et al. (2023)

Compared to coal and oil, there is less scenario consensus for the role of gas, with some seeing an almost complete phase-out by around 2050 while others see continued or increasing supply out to 2100. Because there is such a large diversity in the pathways, we perform a classification and regression tree analysis (CART) to identify, to first order, the most important factors that lead to different levels of cumulative 2020–2100 supply for gas. We complement the analysis by further statistical analyses (an analysis of variance and a cluster analysis) to explore the variations in the role

of gas in the pathways. Our findings show that cases of gas rebound or increase are contingent upon high fossil-CCS and CDR deployment, and are most likely driven by inadequate representation of real-world constraints on CO₂ storage potential and on fossil fuel- and renewable-based technology innovation, adoption, diffusion, and phase-in/-out path dependencies in certain model frameworks and scenario designs. We thus conclude that our analysis lends support for the replacement of the bridge narrative, as proposed by Kemfert et al. (2022), with unambiguous near- and long-term reduction benchmarks for gas production and use

Overall, our findings show governments' plans and projections remain vastly misaligned with pathways consistent with limiting warming to 1.5 °C or 2 °C, and suggest the need to adopt unambiguous near- and long-term reduction benchmarks in coal, oil, and gas production and use alongside other climate mitigation targets.

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2.3. Probabilistic Assessment of Direct Air Capture Deployment

This paper is under review and is authored by Leonardo Chiani, Pietro Andreoni, Laurent Drouet, Katrin Sievert, Tobias Schmidt, Bjarne Steffen and Massimo Tavoni. The full preprint can be found in the annex.

This study examines the uncertainties, costs, and policy conditions surrounding the large-scale deployment of Direct Air Carbon Capture and Storage (DACCS). DACCS offers unique advantages such as permanent CO₂ removal, low land requirements, and transparent accounting, but its future role in climate mitigation remains highly uncertain.

The authors integrate three DACCS technologies (liquid solvent, solid sorbent, and CaO ambient weathering) into the WITCH integrated assessment model. They conduct the first global uncertainty quantification and sensitivity analysis of DACCS, using probabilistic input distributions and novel Optimal Transport-based sensitivity indices. Inputs span four uncertainty dimensions: technological costs/performance, market penetration limits, financing costs, and subsidy design. Two policy environments are tested:



- **NDC scenario:** extrapolation of current climate pledges,
- **LTS scenario:** ambitious long-term net-zero strategies.

The analysis reveals that DACCS deployment exhibits a fat-tailed distribution of outcomes: while most simulations show only modest removals of less than 0.5 GtCO₂ by 2050, there remains a 4–6% probability of reaching gigaton scale by mid-century. The main drivers of deployment are not technological costs but rather subsidies and market growth constraints, with subsidies of at least 425 USD/tCO₂ required to unlock large-scale deployment. In the weaker NDC policy scenario, cumulative subsidies of 1.6–3.6 trillion USD are necessary by 2050, whereas under ambitious long-term strategies this requirement falls to about 0.9 trillion USD. Economically, DACCS deployment entails short- and mid-term losses in GDP and consumption, with net benefits emerging only after mid-century under stringent policy environments; even then, welfare gains remain uncertain and heavily dependent on policy ambition. Overall, the study identifies diffusion and market penetration as the critical bottlenecks, suggesting that without strong policy frameworks and substantial financial support, current DACCS technologies are unlikely to scale fast enough to play a reliable role in global mitigation efforts. See Figure 3.

The results caution against over-reliance on DACCS in weak policy environments: deployment may remain minimal and economically unjustified. In strong climate policy settings, DACCS could contribute meaningfully, though at high public cost and with delayed benefits. The study emphasizes the need to focus on removing diffusion barriers and diversifying technological portfolios, rather than betting solely on incremental cost reductions.



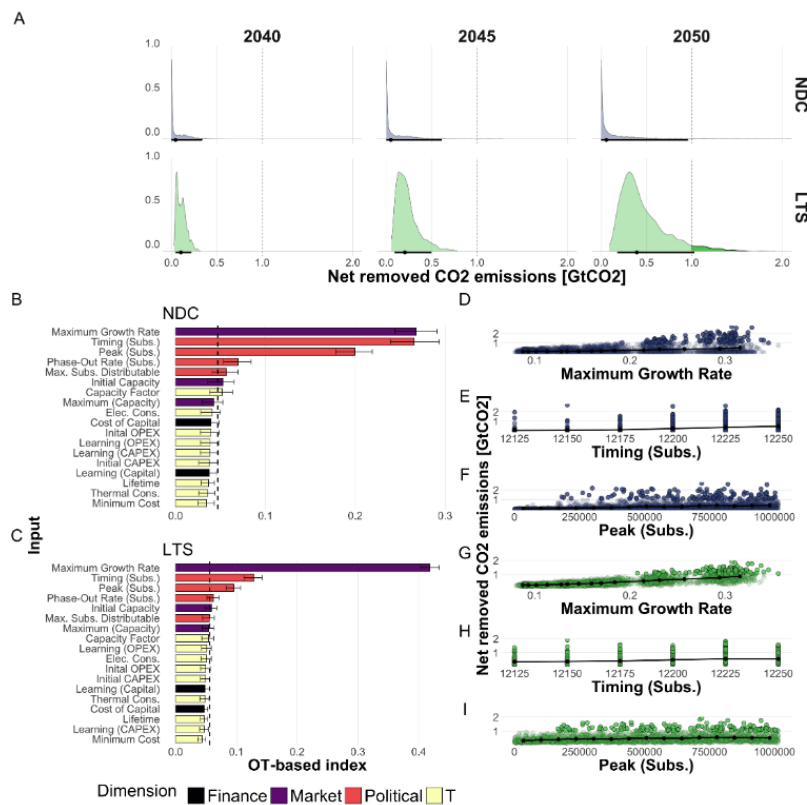


Fig. 2 A. Yearly net CO₂ emissions removed by DACCS between 2040 and 2050 in the two scenarios. Each plot represents the empirical probability density. Transparency identifies the threshold of 1 GtCO₂. The black bars below the plots represent medians and 5th-95th quantile ranges. B-C. Sensitivity analyses for net removed CO₂ emissions in the two scenarios. The x-axis represents the OT-based index. On y-axis, each bar represents the input. Error bars are the 95% bootstrapped confidence intervals. Colours represent the dimension of uncertainty. Inputs are ranked in descending order. Where inputs are differentiated by technology, we consider the maximum OT-based index among them. The dashed vertical line represents the irrelevance threshold. D-E-F. Partial dependency plots in the NDC scenario. The x-axis represents the input value, and the y-axis represents the corresponding net removed CO₂ emissions in 2050. The transparency is the 1 GtCO₂ threshold, and the black line represents the estimated conditioned mean. H-G-I. Partial dependency plots in the LTS scenario.

Figure 3. Source: Chiani et al, (in prep)

2.4. Probabilistic technology cost trajectories for global sensitivity analysis

The work on Task 3.3 of the PRISMA project, completed by UCAM and ETHZ teams in 2024 and presented in the Deliverable 3.2 (Kolesnikov et al., 2024), focused on creating a database of up-to-date probabilistic technology cost forecasts for key low-carbon and clean energy technologies: solar photovoltaics (PV), onshore and offshore wind energy, lithium-ion batteries, proton exchange membrane (PEM) electrolyzers, and light-emitting diode (LED) lighting.

These cost forecasts can be used as inputs into a global sensitivity analysis of integrated assessment models to the uncertainty of technological change. For each technology, forecasts of the global annual average technology cost for the 2024-2050 period are provided for four technology deployment

scenarios representing current growth rate, higher growth rate, low growth rate, and lower growth rate. Each forecast includes five cost trajectories representing the median forecast, as well as the 50% and 95% confidence intervals in the probability distribution. An example of the probabilistic cost forecast for onshore wind presented in Kolesnikov et al. (2024) is shown in Fig. 4.

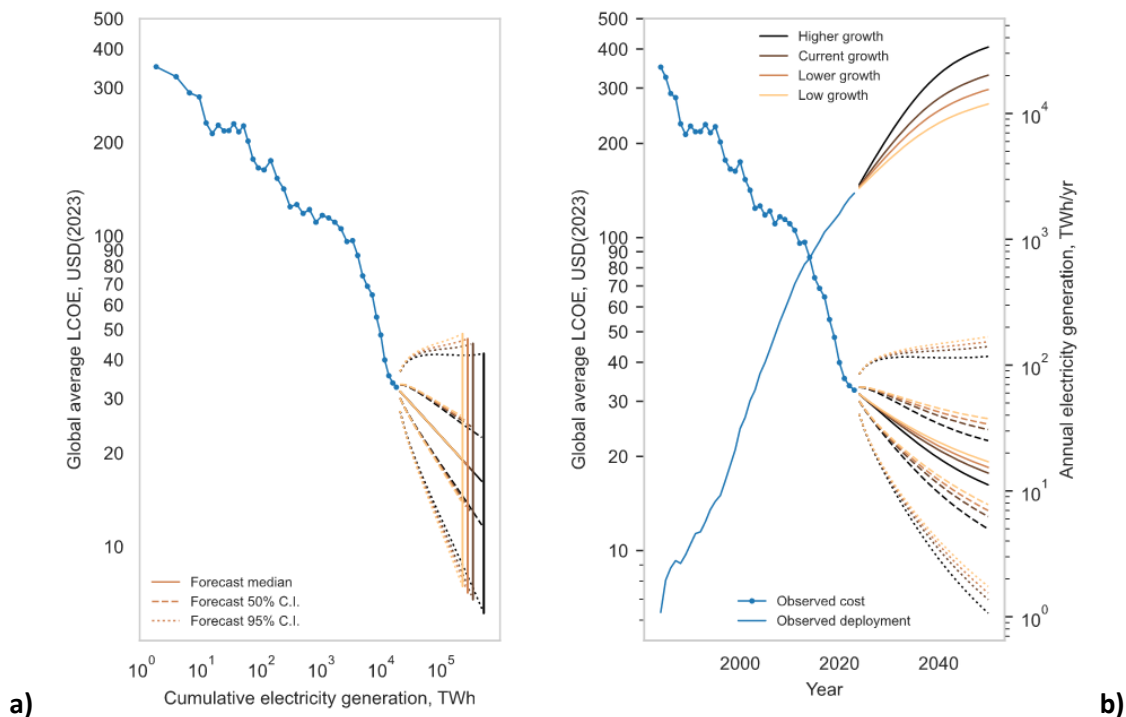


Figure 4— Panel a) shows the historical experience curve, plus four probabilistic cost forecasts, each conditional upon one of the four deployment scenarios. Forecast medians, 50% confidence intervals (C.I.s) and 95% C.I.s are shown. Panel b) shows historical cost (left axis) and deployment (right axis) trajectories over time, plus the four future deployment scenarios and their associated probabilistic cost forecasts. Source: adapted from Kolesnikov et al. (2024).

These probabilistic technology cost forecasts were generated using the stochastic first-difference method, which has been extensively tested and validated against past data and forecasts (see Farmer and Lafond, 2016; Lafond et al., 2018; Way et al., 2022). As described in Kolesnikov et al. (2024), this method accounts for two fundamental sources of uncertainty associated with forecasting future technology costs: 1) uncertainty in the learning rate estimates of a technology at any given time, since these can only ever be based on the data available at the time, which is itself subject to uncertainty; and 2) uncertainty caused by exogenous shocks, such as changes in interest rates, fluctuations in commodity market prices of material inputs, supply chain constraints, or technological breakthroughs elsewhere in the economy. As probabilistic forecasts are generated using a model based on differences rather than levels of learning rate estimates, the confidence intervals provided for the forecasts are consistent with the idea that technology costs develop continuously over time as the result of accumulating both technological progress and exogenous shocks.

The 2.5%, 25%, 50%, 75% and 97.5% cost trajectories provided with each forecast can be used directly as exogenous scenario inputs in the global sensitivity analysis of the IAMs to the assumptions about future technology costs. However, it is essential to consider that these trajectories are conditional on future technology deployment scenarios used to develop these forecasts. It would not be appropriate

to use these forecasts with deployment scenarios that differ greatly from those provided. If an IAM uses different assumptions about future technology deployment, a more appropriate way to test the sensitivity of the model to the uncertainty in future technology costs is to generate probabilistic cost forecasts within the model, applying the stochastic cost forecasting methodology described above to technology cost and deployment at each step, while ensuring that the resulting trajectories are consistent with the historically observed experience curve trends.

The latter approach is currently being implemented by the CMCC team in the WITCH model. Integrating up-to-date probabilistic cost forecasts for the key low-carbon and clean energy technologies into the model will enable testing the sensitivity of the model to the uncertainty in future technology costs, advancing the foundations for improved representation of technological change and uncertainty in IAM modelling and analysis.

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2.5. Hindcasting-based probabilistic forecasting of the future electricity system in 31 European countries

This is an extended summary of the manuscript by Wen X., Jaxa-Rozen M., Zielonka N., Trutnevyte E. to be completed and submitted to a peer-reviewed journal in the coming months.

Summary

There have always been disparities between the modelled energy projections and real-world transitions. Even when projections are framed as futures that could happen and not will happen, the sets of past projections were either too narrow to depict the future uncertainty, or too wide to be informative. To address this, we demonstrate how empirical probabilistic density forecasting could be used with a bottom-up cost-optimization energy system model to produce probabilistic projections, using hindcasting. We apply our approach on D-EXPANSE electricity sector models in 31 European countries. By applying empirical density forecasting methods across multiple countries and quantities, we aim to elicit robust insights on the applicability of probabilistic uncertainty forecasting in technology-rich, cost-optimization models.



Introduction

The optimization-based models of electricity systems are commonly used to generate electricity projections to support policy decisions, particularly at the national level [1]. In retrospective analyses, it is often acknowledged that there are valid reasons why projected outcomes differed consistently from historical transitions as projections are not the tools to predict what will happen [2–4]. However, there have been instances in the past where these projections proved to be biased and overly confident, underestimating future uncertainties [4], or they exhibited too wide variation bounds without distinguishing which projections are more likely than others [5]. While pioneering efforts have introduced probabilistic uncertainty forecasting methods for energy projections in the United States [6], it remains unknown to what extent these approaches can be applied to other countries and integrated into energy models rather than being applied post-hoc to the projections generated by the models. In this study, we use the D-EXPANSE cost-optimization modeling framework to demonstrate and evaluate empirical density forecasting methods for electricity sectors of 31 European countries.

Methods

To carry out the empirical probabilistic forecasting for the national electricity system transitions until 2035, we use a cost-optimization modeling framework D-EXPANSE [2] and incorporate empirical density intervals around the model projections [6]. Our focus is on electricity sector transitions over 1990 – 2019 (for hindcasting) and then over 2020 – 2035 (for probabilistic forecasting) across 31 European countries: EU27, Iceland, Norway, Switzerland, and UK.

First, by comparing the modelled projections of D-EXPANSE with the real-world transitions, we collected the forecasting errors of each quantity (model output): the installed capacity and annual generation of each electricity-generating technology in the country. Second, the empirical probabilistic forecasting model was then built to generate the density intervals around the model projections by employing multiple forecasting methods with different error types and error distribution assumptions. The error types included mean error (ME), mean logarithmic error (MLE), and symmetric mean percentage error (sMPE). The error distribution assumptions included nonparametric distribution [7], parametric (Gaussian) distribution, and Chebyshev inequality-based distribution [7,8]. Then, the proposed forecasting methods were evaluated through out-of-sample testing across different training and testing horizons. The density intervals were evaluated by the weighted interval score (WIS), which is commonly used to evaluate the performance of the prediction intervals [9]. Finally, the density intervals around the model projections until 2035 were generated by implementing the best performed forecasting method for each quantity in each country.

Results

In this study, we employed multiple methods to forecast the empirical density intervals of each model projection in 31 European countries. For example, regarding the installed capacity for solar PV (Figure 5), the best performing are ME-based methods (marks in blue), while the MLE-based methods (marks in yellow) have usually the highest WIS, indicating the worst performance. Among all the methods, Chebyshev's inequality-based ME method and nonparametric-based ME method outperform other methods. Chebyshev's inequality-based ME method performs the best in 17 countries, the second best in 10 countries and the third best in one country. The corresponding values for nonparametric-based ME method are six (the best), 16 (the second best) and three (the third best). In terms of the annual generation of gas-based generation, the performance differences are less evident compared to the installed capacity of PV since the marks are less deviated vertically in most of the countries. Also, there



are more than two methods that perform relatively well. The nonparametric-based ME, parametric-based ME, nonparametric-based sMPE and Chebyshev inequality-based ME methods have the best performance in no less than five countries.

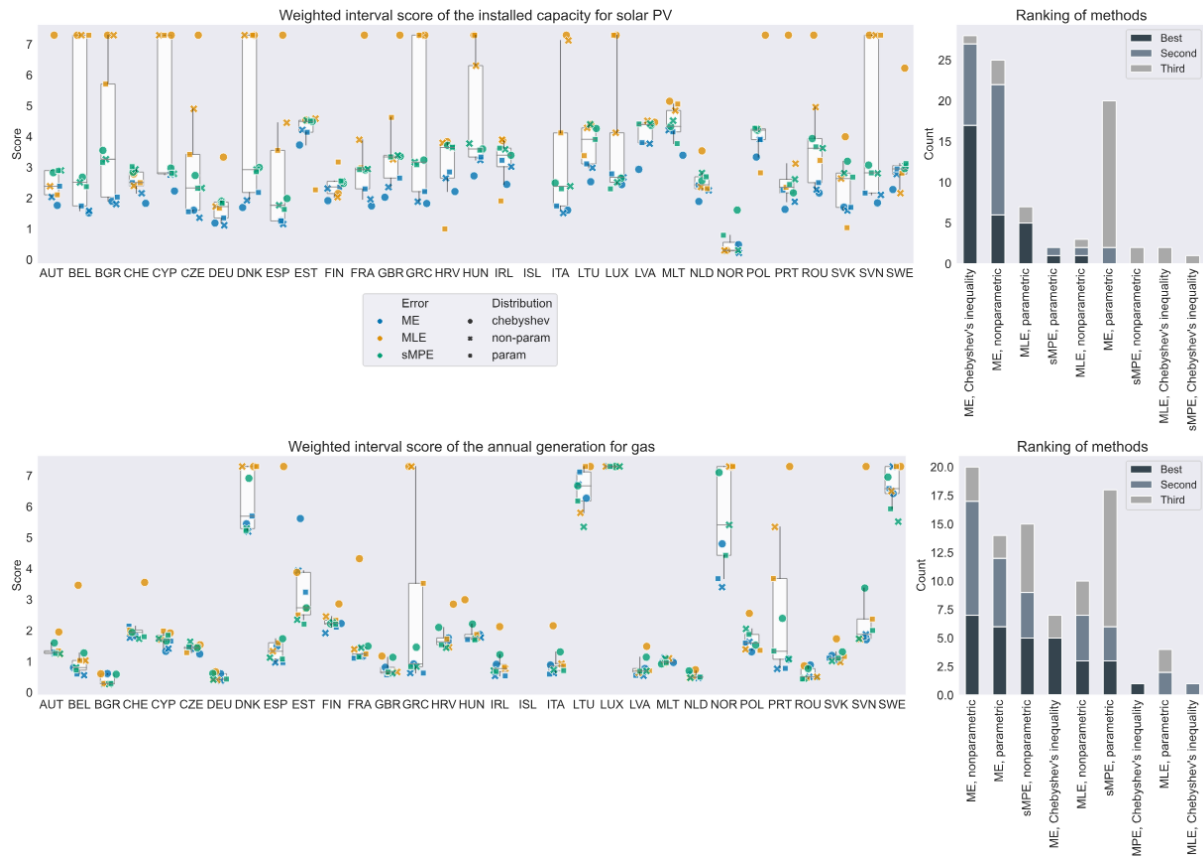


Figure 5. Performance of probabilistic projection methods of two quantities: the installed capacity for solar PV (represented by the upper figures) and the annual electricity generation for natural gas-based generation (represented by the bottom figures). The left-hand side scatter and box plots show the WIS of each density forecasting method for the two quantities in each country. A lower WIS indicates a better performance of a method. The colors show different error types and shapes show different distribution assumptions. The right-hand side bar plots show, for these two quantities, how many countries reach the best, the second best, the third best performance by implementing a certain method.

To obtain the empirical density forecasting until 2035 or later, we employ the best performed method for each quantity in the country. Regarding the installed capacity for solar PV, Chebyshev's inequality-based ME method is used in many countries, such as Belgium, UK and Greece (Figure 6 (a)). The growth rate is more drastic in Belgium than in the UK and Greece, while the wider density intervals indicate a larger uncertainty in the UK. The nonparametric-based ME is used to project the annual generation for gas in Belgium, Germany and Greece (Figure 6 (b)). Without the assumption for the error distribution, the nonparametric methods tend to show less regular density intervals since the intervals follow



exactly the historical density variations.

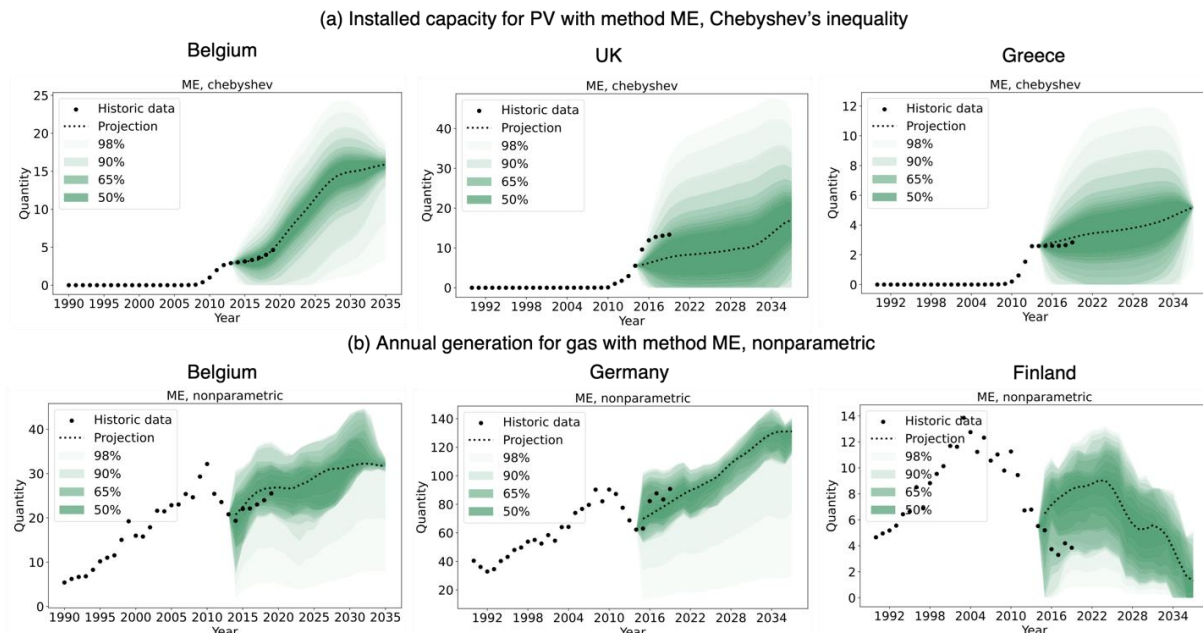


Figure 6. The empirical density forecasting until 2035: (a) the installed capacity for solar PV with Chebyshev's inequality-based ME method in Belgium, UK and Greece; and (b) the annual electricity generation for gas with nonparametric-based ME method in Belgium, Germany and Finland.

Conclusions

In this study, we introduced an approach for probabilistic uncertainty forecasting in bottom-up cost-optimization modeling by incorporating empirical density intervals in the model projections, using hindcasting. To analyze the national electricity sectors in 31 European countries from 1990 to 2019, we conducted a retrospective modeling exercise with the D-EXPANSE model. We developed multiple empirical density forecasting methods that take into account various projection error types and error distributions. To evaluate the accuracy of these model output projections, we employed retrospective modeling on out-of-sample testing. The results demonstrate that in order to obtain the most appropriate density intervals around the projections, it is necessary to select different empirical density forecasting methods for each quantity in the country. This research provides valuable insights into the effective capture and presentation of probabilistic uncertainty projections by bottom-up models, that could ultimately improve projections for decision-making.

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3. Social choices and decisions under uncertainty

3.1. Climate Policy under Tipping Risk and Temporal Risk Aversion

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When it comes to decision-making, risk is all around. In intertemporal settings, the absolute risk aversion with respect to aggregate intertemporal risk is called the temporal risk aversion (Bommier et al., 2015). The standard discounted expected utility model assumes temporal risk-neutrality (Ahn, 1989). This assumption has large implications as it implies that the decision-maker has no preference on the correlation between individual risks. Introducing absolute risk aversion with respect to intertemporal utility, i.e. temporal risk aversion, on the other hand, allows to consider risk bearing on aggregate intertemporal utility.



A prominent example of intertemporal social risk management is climate policy-making. A major concern of climate policy-making is the possibility of non-linearities such as tipping points in the climate system. Once some thresholds for greenhouse gas concentrations in the atmosphere are exceeded, the state of the climate system could be radically and irreversibly altered. Tipping elements with significant economic implications have been identified, including the slowdown of the Atlantic Meridional Overturning Circulation, the West Antarctic ice sheet disintegration, the Amazon rainforest dieback, or the Greenland ice sheet disintegration (Arias et al., 2021). In the states of the world where the tipping point occurs, the welfare of all subsequent generations is affected by this qualitative regime change. Consequently, considering absolute risk aversion with respect to intertemporal utility becomes imperative due to the substantial impact on intertemporal welfare.

In this work, we investigate the implications of absolute risk aversion with respect to intertemporal utility, i.e. temporal risk aversion, in the presence of a stylized climate tipping risk affecting productivity irreversibly. We analyze both analytically and numerically why, how and by how much two social planners, i.e. a temporally risk-neutral and a temporally risk-averse planner, differ in their optimal policy under risk. We focus on a specific type of risk: a climate tipping risk. We use a dynamic stochastic climate economy model (Guivarch and Pottier, 2018; Taconet et al., 2021) and extend it to an alternative social welfare function which allows the analysis of temporal risk aversion: the risk-sensitive preferences axiomatized in Hansen and Sargent (1995). By comparing optimal climate policies under risk-sensitive preferences with those under the standard additive form of expected discounted utility, which assumes temporal risk-neutrality, we shed light on the implications of temporal risk aversion for policy design.

We find that, in the presence of a tipping risk, optimal climate policy is more stringent under temporal risk aversion, in order to reduce all present and future probabilities of crossing the tipping point and avoid a situation where all generations are badly off. The social planner under risk-sensitive preferences is willing to sacrifice more today to reduce all present and future probabilities of crossing the tipping point to avoid a situation of low overall intertemporal utility level. The difference in optimal climate policy between the two planners increases more than proportionally to the increase in the possible shock or in the temporal risk aversion (Figure 7, top). Under our benchmark calibration, a change from additive to risk-sensitive preferences implies a 30% increase in the social cost of carbon (SCC) for a 10% irreversible increase in the damage factor. Switching from additive to risk-sensitive preferences under a 10% possible shock is equivalent to a 5 percentage points increase in the shock if we keep additive preferences. The difference between the two social choice criteria increases steeply with risk. Furthermore, other things being equal, a 50% decrease in pure time preference (from 1.5% to 1% yearly) is needed to obtain the same optimal policy under additive preferences as under risk-sensitive preferences for a 10% tipping risk and under our benchmark calibration (Figure 7, bottom). Thus, a change in the structure of the social welfare function can be directly compared to a change in the value of some parameters that have been highly debated.



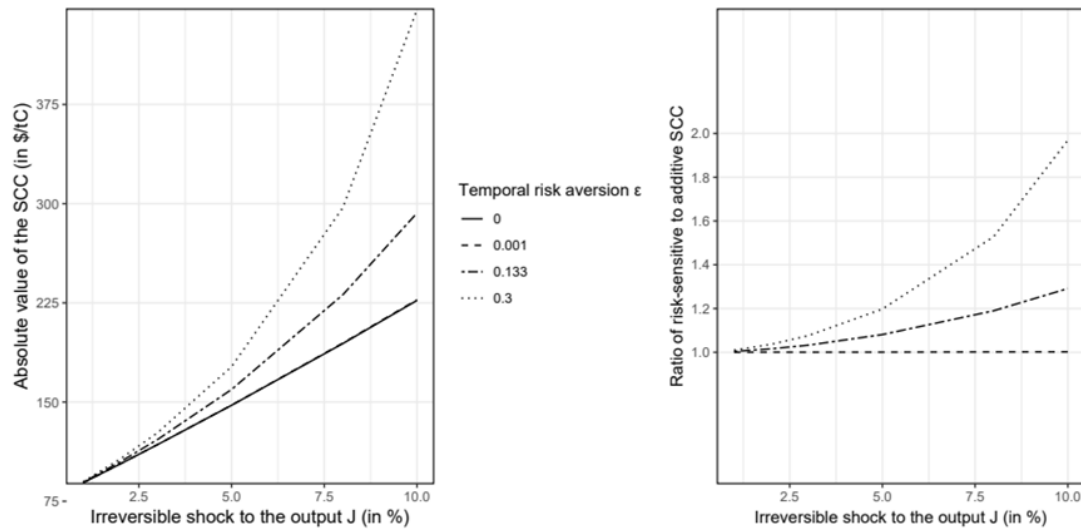


Figure 1: Absolute values of the additive and risk-sensitive SCC (in \$ per tC) at initial time (left) and ratio of the risk-sensitive SCC to the additive SCC (right) for various J and ϵ under our benchmark calibration ($\eta = 1.5$, $\rho = 1.5\%$). The curves overlap for the two smallest values of ϵ in the left-hand graph. Same graphs with a wider range for J are given in Appendix E.1.

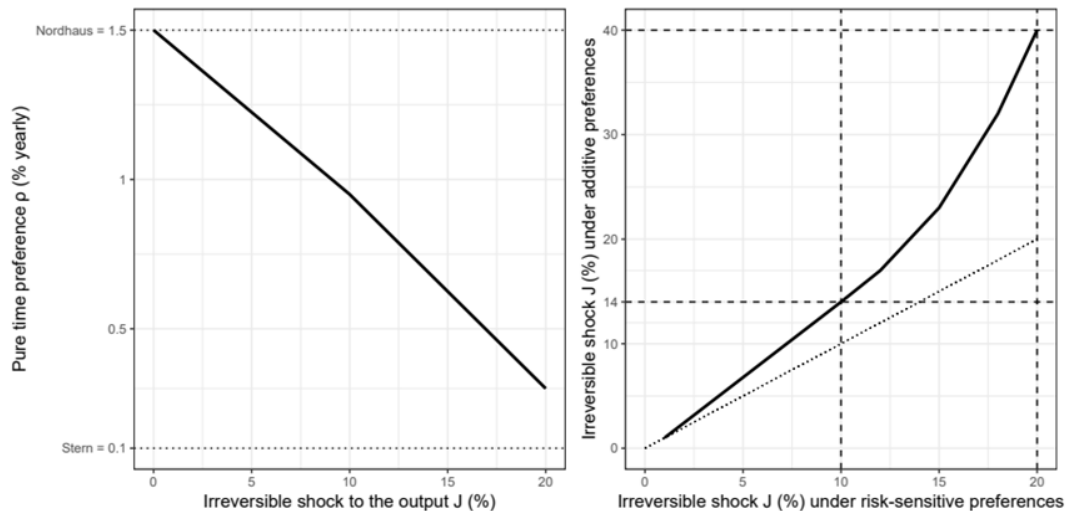


Figure 2: Equivalence in ρ (left) and J (right) needed to obtain the same SCC at initial time under additive and risk-sensitive preferences under our benchmark calibration. On the left, we represent the pure time preference (ρ) that is needed under additive preference (all else being equal) to match the risk-sensitive SCC for various J . On the right, we represent the irreversible shock J that is needed under additive preference (all else being equal) to match the risk-sensitive SCC for various J . The dotted line from the right-hand graph is the identity function.

Figure 7. Source: Figures from Fillon et al. (2023)

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3.2 Climate Policy Under Model Misspecification

This paper is under review and is authored by Jacopo Ghirri, Massimo Marinacci and Massimo Tavoni. A preprint version is available at <https://doi.org/10.21203/rs.3.rs-6813235/v1>.

Climate policy is highly sensitive to how different uncertainties are addressed (Drouet et al, 2015). The impact of different sources of uncertainty, ranging from parameter to model uncertainty, has been thoroughly studied (Drouet et al, 2015; Drouet et al., 2022; Kunreuther et al., 2013), but little work has been conducted in the direction of addressing the deep, overarching uncertainties induced by Model Misspecification (Tavoni and Valente, 2022; Cerreia-Vioglio et al., 2022). Within the framework of Model Misspecification, we aim to capture the structural uncertainties that affect our models. These may stem from simplifications, approximations, a limited understanding of underlying processes, or even incorrect assumptions. This research explores how decision-makers respond when confidence in model outputs is low. In particular, it examines how such mistrust influences the selection of long-term emission targets, and the degree of flexibility allowed in meeting those targets over time.

We conducted a cost-benefit analysis, evaluating the estimates of climate damages and costs of mitigation for a selection of climate policies (see Figure 8). Estimates are obtained from combining emulators fitted on a selection of scenarios from Integrated Assessment Models (IAMs), with two leading econometric approaches for quantifying the economic damages of Climate Change (Burke et al., 2015; Howard and Sterner, 2017).



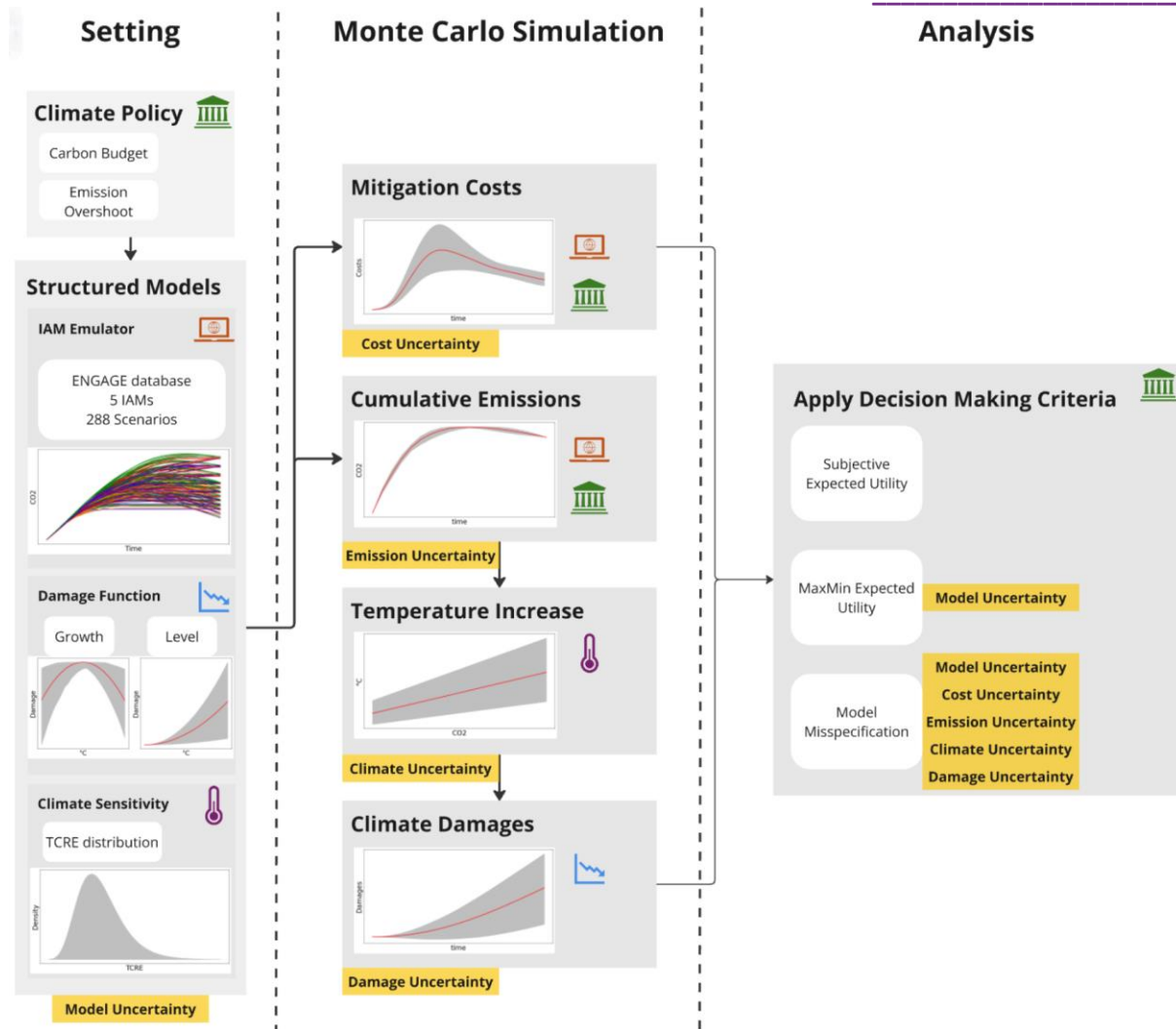


Figure 8: Methodology Overview

We then compared the policy recommendations derived from a decision-making criterion that explicitly accounts for concerns of Model Misspecification (Cerreia-Vioglio et al., 2022) against those obtained using two other established approaches, one blind to uncertainties (Cerreia-Vioglio et al., 2013), the other only expressing concerns of Model Uncertainty (Gilboa and Schmeidler, 1989). The analysis shows that significant uncertainty surrounding long-term climate damages leads decision-makers concerned about model reliability toward more stringent climate targets, such as carbon budgets consistent with staying well below 2°C. Furthermore, overshooting these budgets, even when ambitious, becomes less preferable as the outcomes of delaying actions become more uncertain (See Figure 9).

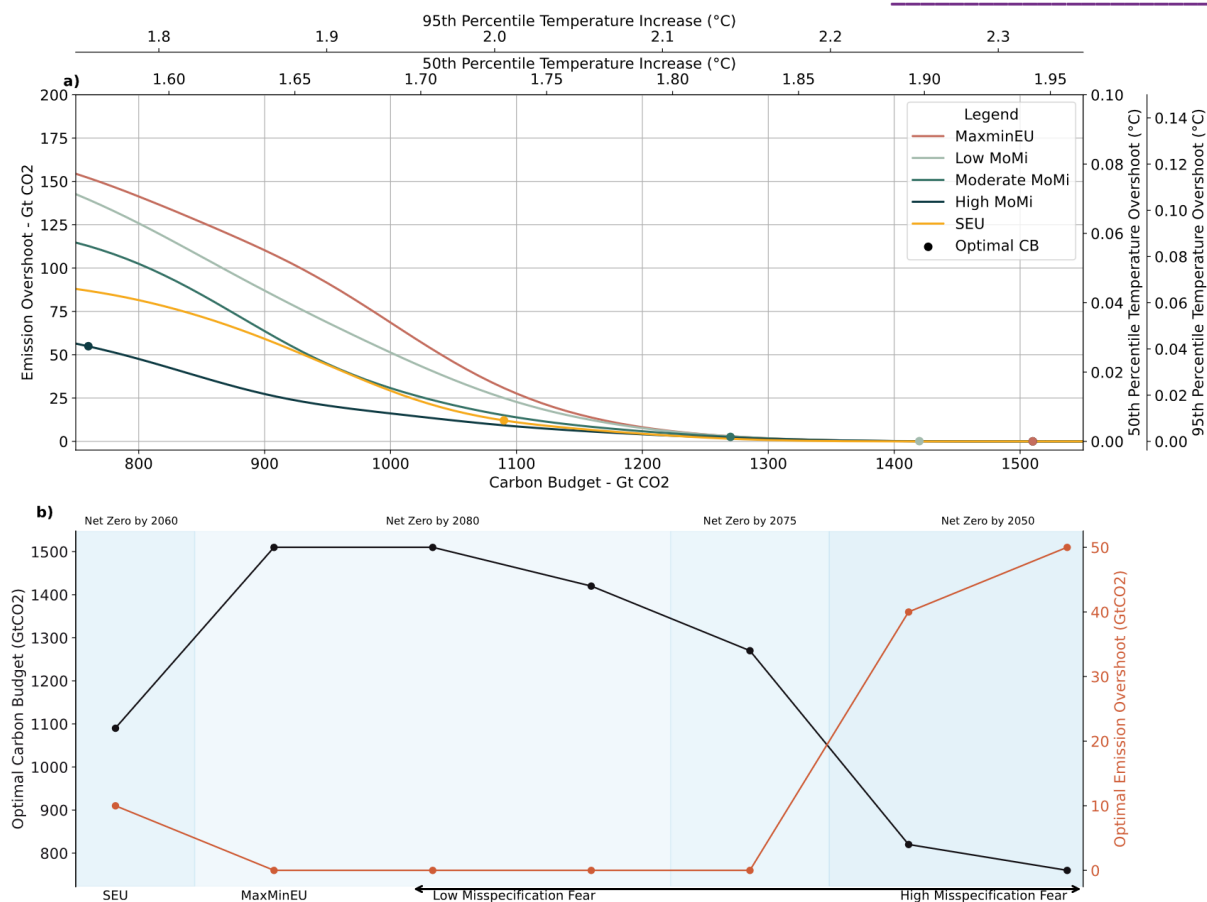


Figure 9: Impact of the model specification on the emission overshoot and the optimal carbon budget.

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Appendix

This appendix features the full texts of:

- Achakulwisut, P., Erickson, P., Guivarch, C. et al. Global fossil fuel reduction pathways under different climate mitigation strategies and ambitions. Nat Commun 14, 5425 (2023). <https://doi.org/10.1038/s41467-023-41105-z>
- Chiani et al. Uncertainties, Costs, and Bottlenecks of Large-Scale Direct Air Capture of CO₂
- Romain Fillon, Céline Guivarch, Nicolas Taconet. Optimal climate policy under tipping risk and temporal risk aversion. Journal of Environmental Economics and Management, 2023, 121, pp.102850. [10.1016/j.jeem.2023.102850](https://doi.org/10.1016/j.jeem.2023.102850)
- Ghirri et al. Climate Policy under Fear of Model Misspecification



Global fossil fuel reduction pathways under different climate mitigation strategies and ambitions

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 Check for updatesPloy Achakulwisut ^{1,2}✉, Peter Erickson¹, Céline Guivarch ³,
Roberto Schaeffer ⁴, Elina Brutschin ⁵ & Steve Pye ⁶

The mitigation scenarios database of the Intergovernmental Panel on Climate Change's Sixth Assessment Report is an important resource for informing policymaking on energy transitions. However, there is a large variety of models, scenario designs, and resulting outputs. Here we analyse the scenarios consistent with limiting warming to 2 °C or below regarding the speed, trajectory, and feasibility of different fossil fuel reduction pathways. In scenarios limiting warming to 1.5 °C with no or limited overshoot, global coal, oil, and natural gas supply (intended for all uses) decline on average by 95%, 62%, and 42%, respectively, from 2020 to 2050, but the long-term role of gas is highly variable. Higher-gas pathways are enabled by higher carbon capture and storage (CCS) and carbon dioxide removal (CDR), but are likely associated with inadequate model representation of regional CO₂ storage capacity and technology adoption, diffusion, and path-dependencies. If CDR is constrained by limits derived from expert consensus, the respective modelled coal, oil, and gas reductions become 99%, 70%, and 84%. Our findings suggest the need to adopt unambiguous near- and long-term reduction benchmarks in coal, oil, and gas production and use alongside other climate mitigation targets.

The 2021 Glasgow Climate Pact reaffirmed the commitments of national governments to limit global-mean temperature rise to 1.5 °C¹, and recent developments in climate governance suggest increasing policy attention on fossil fuels in the years ahead. For example, in 2021, the 26th Conference of the Parties (COP26) to the United Nations Framework Convention on Climate Change (UNFCCC) saw a launch of the first-ever alliance of governments working together to “facilitate a managed phase-out of oil and gas production”². COP26 culminated in an Agreement text that explicitly mentioned fossil fuels for the first time, with countries committing to accelerate efforts “towards the phasedown of unabated coal power”¹. At COP27, more than 80 countries supported India’s proposal to apply this phase-down language to all fossil fuels³. In March 2023, the UN Secretary-General urged all

countries to establish a “global phase-down of existing oil and gas production compatible with the 2050 global net zero targets”⁴. At the same time, global fossil fuel-derived carbon dioxide (CO₂) emissions rose to the highest level in history in 2021–2022⁵, and the global levels of fossil fuel production being planned and projected by governments’ national energy outlooks remain vastly in excess of levels consistent with limiting warming to 1.5 °C⁶. The 2022–2023 global energy crisis has also sparked a reappraisal of energy policies and priorities worldwide. It remains unclear whether this will serve to accelerate the clean energy transition or lock in fossil fuel dependence⁷, with many countries expanding natural gas production or import capacity and others reviving coal use in their short-term responses⁸. This occurs against a backdrop of long-standing and growing tensions as to whether natural

¹Stockholm Environment Institute, Seattle, WA, USA. ²Stockholm Environment Institute, Bangkok, Thailand. ³International Research Center on Environment and Development (CIRED), École des Ponts, Nogent-sur-Marne, France. ⁴Centre for Energy and Environmental Economics (CENERGIA), COPPE, Universidade Federal do Rio de Janeiro, Rio de Janeiro, Brazil. ⁵International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria. ⁶UCL Energy Institute, University College London, London, UK. ✉e-mail: ploy@sei.org

gas is a “bridge fuel” to a low-carbon future or a “bridge to nowhere”^{9–14}.

Consequently, although policymakers now broadly share the common goal of striving for a net-zero future, new debates are emerging around the speed and trajectory of the necessary energy transitions, including the associated reduction pathways for coal, oil, and natural gas (also known as fossil gas or fossil methane gas; hereafter referred to as gas) supply and demand^{14–18}. Such debates are increasingly informed by process-based integrated assessment models (IAMs), which have become widely used to provide policy-relevant insights into how the world’s energy and land-use systems can be transformed in the most cost-effective way to achieve the Paris Agreement’s goal of limiting long-term warming to “well below 2 °C and pursuing efforts to limit the temperature increase to 1.5 °C above pre-industrial levels”^{19,20}.

To meet a given carbon budget – the cumulative amount of CO₂ emissions that can be emitted until the end of the century or until net-zero attainment – consistent with limiting global warming to a certain temperature threshold, IAMs generally rely on different combinations and extents of the following major strategies: (1) phasing out fossil fuels from the energy supply, buildings, transport, and industry sectors; (2) transforming agricultural and land-use practices; (3) reducing energy and material consumption; and (4) relying on carbon dioxide removal (CDR) and carbon capture and storage (CCS) deployment. Non-CO₂ greenhouse gases (GHGs) such as methane and other short-lived climate forcers also influence the level of peak warming, and their emissions reductions are another important mitigation lever²¹. The relative importance of different mitigation strategies reflects differences in the underlying model framework, scenario design, and input parameters and assumptions such as technological performance and adoption, economic relationships, and cost optimization^{22–24}. The majority of low-carbon scenarios produced by IAMs rely extensively on CDR, mostly through bioenergy combined with carbon capture and storage (BECCS) and land sequestration; a few scenarios also employ direct air capture with carbon capture and storage (DACCS)^{21,25}. However, the feasibility of large-scale CDR and CCS deployment remains highly uncertain, with growing concerns that we would be locking in continued fossil fuel dependence and global temperature increases above 2 °C if they were to fail^{26–30}. Intensive land use for bioenergy or for carbon sequestration by the Agriculture, Forestry, and Other Land Use (AFOLU) sector could also lead to land degradation, food insecurity, biodiversity loss, and water scarcity^{28,29,31}.

The Working Group III (WGIII) contribution to the Intergovernmental Panel on Climate Change (IPCC)’s Sixth Assessment Report (AR6) compiled and assessed 3131 scenarios generated by almost 100 different model versions from more than 50 model families, with varying regional scope and temperature outcomes²¹. This new scenarios database is likely to be extensively used to inform socio-political discourse on energy system transformations in the years ahead, including on identifying fossil fuel reduction pathways that are consistent with the Paris Agreement^{32,33}. However, there is a large variety of IAMs and associated modelling approaches and assumptions, resulting in important differences in the outputs. Moreover, there is an increasing risk that key assumptions and the resulting model-based insights become implicitly accepted by researchers and policymakers without a clear understanding or critical evaluation of their real-world implications, feasibility, and desirability³⁴.

In this work, we explore what the AR6-assessed scenarios consistent with limiting warming to 2 °C or below say about the speed, trajectory, and feasibility of different global coal, oil, and gas reduction pathways and why. We first summarise the trends across all modelled pathways under three different temperature outcomes, and perform a classification and regression tree analysis to identify the most important factors influencing the levels of cumulative supply for a given fossil fuel. We then perform additional statistical analyses to further

explore the model parameters and assumptions associated with different transition pathways for gas. Next, we evaluate the sensitivity of the modelled fossil fuel reduction trajectories to different mitigation scenario storylines and assumptions, including CDR reliance, and their feasibility with respect to geophysical, economic, technological, socio-cultural, and institutional considerations. We then close with a discussion of the policy implications of our findings.

Results

Global fossil fuel reduction pathways in scenarios that likely limit warming to 2 °C or below

Chapter 3 of the IPCC AR6 WGIII report vetted 1686 global scenarios, of which 1202 provided sufficient information for a temperature outcome categorization, ranging from C1 to C8²¹. Here we focus on the categories with the three lowest temperature outcomes: C1 – limit warming to 1.5 °C in 2100 with a likelihood greater than 50%, with no or limited overshoot; C2 – limit warming to 1.5 °C in 2100 with a likelihood greater than 50%, with high overshoot; and C3 – limit peak warming to 2 °C with a likelihood greater than 67%²¹. We analyse all scenarios in the C1–C3 ensemble and consider them to be relevant to the Paris Agreement’s temperature limits, even if some individual scenarios may be considered to not be fully Paris-compliant depending on one’s interpretation of its long-term temperature goal and of its other objectives, as well as judgement on the probability, overshoot, and timing of the temperature change³⁵. Given the Glasgow Climate Pact’s emphasis on the 1.5 °C limit, we pay particular attention to the C1 scenarios in the main text. Of the 541 vetted C1–C3 scenarios, 94 C1, 131 C2, and 310 C3 scenarios report primary energy supply from coal, oil, and gas. Since all but one C3 scenario analysed in this study are generated from IAMs that typically include non-energy uses of fossil fuels under their reporting of the “Primary Energy|xx” variable (see Methods for details), we broadly interpret this variable to represent total supply intended for all uses. However, the completeness with which non-energy uses are accounted for and reported varies between different models and could have significant implications for the resulting fossil fuel reduction pathways under a given carbon budget. Non-energy uses can lead to either long-term carbon storage in stable physical products or eventual combustion (e.g., incineration of discarded plastics), with historical estimates suggesting that around 0.02% of coal, 8.02% of oil, and 1.86% of gas produced do not lead to eventual carbon emissions³⁶.

Figure 1 shows the individual, median, and interquartile range (IQR) 2010–2100 pathways, as well as boxplot distributions of the cumulative 2020–2100 values, of the global coal, oil, and gas supply as modelled by the C1–C3 scenarios (see Supplementary Figs. 1 and 2 for boxplot distributions of the annual values at certain years and of the peak years of supply, respectively). Showing the median pathway provides one way to succinctly communicate the average trajectory within a given scenario ensemble. However, this approach has limitations³⁷, especially because the AR6 ensemble is unstructured and does not represent a statistical sample: it merely reflects the options that have been explored in the underlying studies, which are represented by different model families and scenario designs and protocols to varying degrees (Supplementary Fig. 3). Moreover, while the modelled pathways of different mitigation options within a given scenario are internally consistent for meeting a certain carbon budget, the median pathways of different variables calculated from a set of scenarios may not be. Given this and the diversity in the model outputs, the median pathways shown in Fig. 1 should be considered for illustrative purposes only, as we will later explore how subsets of or individual scenarios diverge from them.

As shown in Fig. 1, across the C1–C3 scenarios, the global supply of coal and oil generally decline substantially and rapidly between now and mid-century, followed by a more gradual and variable reduction over time. More stringent temperature limits necessitate faster and

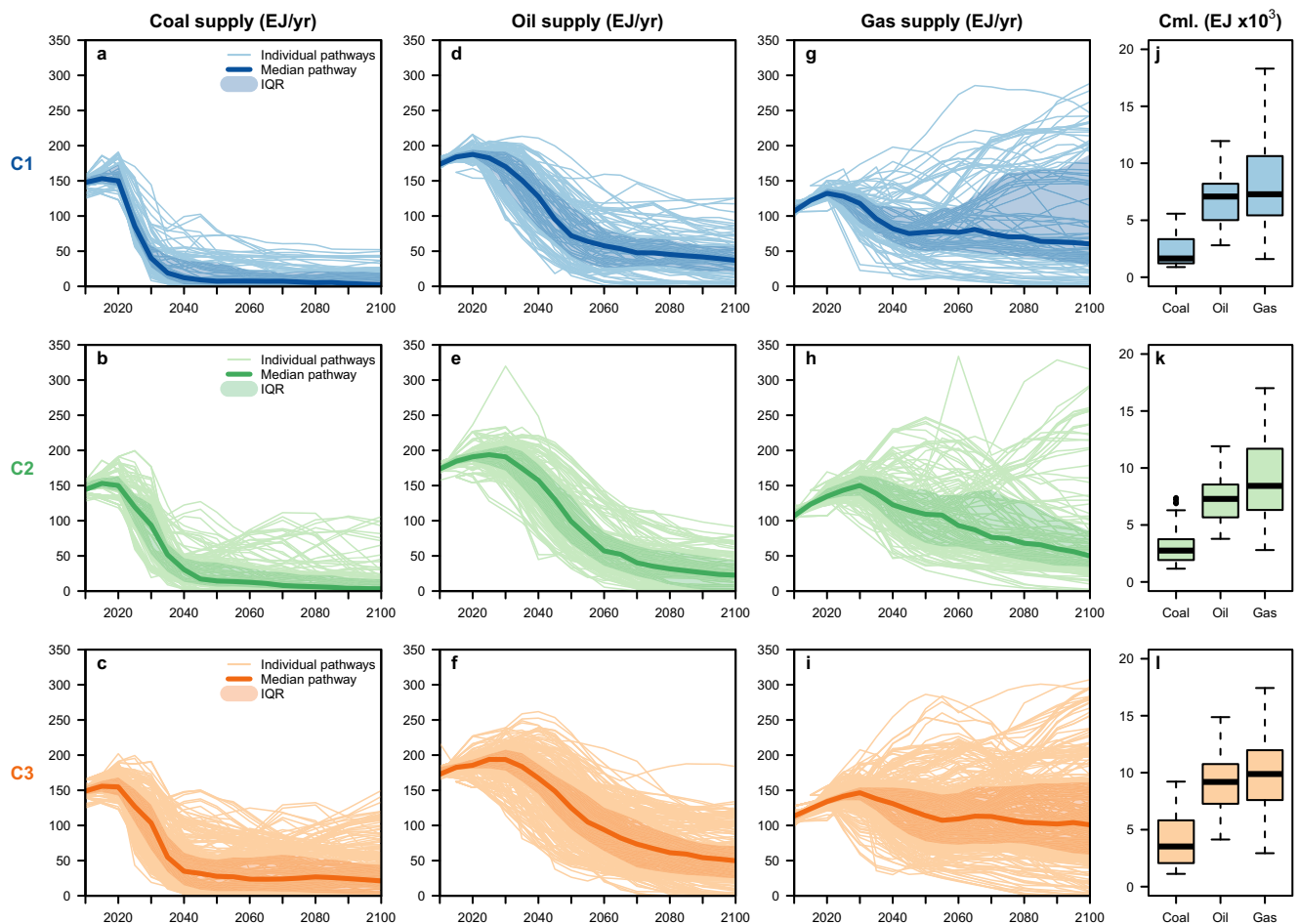


Fig. 1 | Global primary energy supply (in exajoules, EJ) from coal, oil, and gas as modelled by the AR6-assessed mitigation scenarios consistent with limiting warming to 2 °C or below. In panels a–i, the 2010–2100 annual timeseries of the following are plotted at 5-year intervals within a given temperature category (C1–C3): individual pathways (light lines); median pathways (dark lines); and the interquartile range (IQR, shadings). Panels j–l show the boxplot distributions of the

2020–2100 cumulative primary energy supply from coal, oil, and gas across the scenario ensemble within each temperature category. The horizontal center line depicts the median, the box spans the IQR between the 25th percentile (Q1) and 75th percentile (Q3), the lower whisker represents the minimum value or Q1 – 1.5 × IQR (whichever is larger), and the upper whisker represents the maximum value or Q3 + 1.5 × IQR (whichever is smaller).

greater reductions. Compared to coal and oil, there is less scenario consensus for the role of gas, with some seeing an almost complete phase-out by around 2050 while others see continued or increasing supply out to 2100. The scenarios also model varying levels of coal, oil, and gas supply that can be coupled to CCS at the point of combustion (Supplementary Figs. 4 and 5). Because there is such a large diversity in the pathways, we perform a classification and regression tree analysis (CART)³⁸ to identify, to first order, the most important factors that lead to different levels of cumulative 2020–2100 supply for a given fossil fuel. We choose to employ CART here due to its ability to combine statistical rigour with an accessible and visual interpretation of the results. The independent variables selected for inclusion are those that are frequently discussed in the literature^{21,23,39} and/or judged to likely influence the level of fossil fuel dependence (see Methods). The CART results are shown in Fig. 2 (C1) and Supplementary Figs. 6–11 (C2–C3).

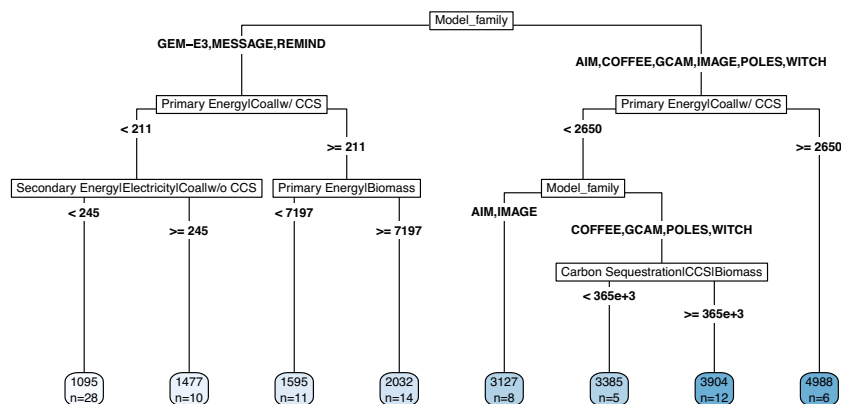
Across the C1–C3 scenarios, global coal supply on average peaks around 2015 (Supplementary Fig. 2) and rapidly declines (the fastest of all three fuels), with the median pathway reaching values below 10 exajoules per year (EJ/yr) in the C1 scenarios, and below 35 EJ/yr in the C2–C3 scenarios, after 2040 (Fig. 1a–c). Coal without CCS is largely eliminated by 2035–2040 (Supplementary Fig. 4). CART reveals that C1–C3 scenarios allowing relatively higher levels of cumulative coal supply are associated with certain model families and higher levels of coal coupled to CCS (Fig. 2a and Supplementary Figs. 6 and 7). For

example, six C1 scenarios with the highest levels of cumulative coal supply (around 5000 EJ) are associated with the AIM and GCAM model families and with cumulative coal coupled to CCS greater than or equal to 2650 EJ.

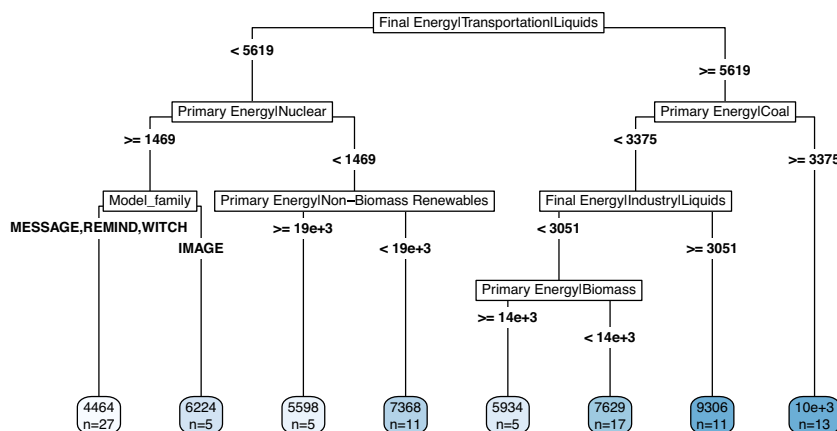
For oil, global supply on average peaks around 2020 for the C1 scenarios and around 2030 for the C2–C3 scenarios (Supplementary Fig. 2) followed by a steep decline out to mid-century, slower than coal but faster than gas (Fig. 1d–f). In general, C1 scenarios with the highest levels of cumulative oil supply are associated with higher oil demand for transportation and non-energy industry use and with higher coal supply; those with lower oil supply are associated with lower transportation demand, higher nuclear energy supply, and certain model families (Fig. 2b). For the C2 and C3 scenarios, higher oil levels are associated with certain model families (AIM, COFFEE, GCAM, REMIND, TIAM, and WITCH), higher gas supply, higher levels of fossil fuel use coupled to CCS (“fossil-CCS”), and certain scenario projects (Supplementary Figs. 8 and 9).

Among the three fuels, the pathways for gas display the largest variability. Nevertheless, global gas supply on average peaks around 2025, 2030, and 2035 for the C1, C2, and C3 scenarios, respectively (Supplementary Fig. 2). In the majority of scenarios, gas supply not coupled to CCS at the point of combustion peaks in 2020 and follows a similar decline trajectory to that of oil (Supplementary Fig. 4), while gas coupled to CCS generally increases out to mid-century

a) CART decision tree for 2020-2100 cumulative coal supply in C1 scenarios



b) CART decision tree for 2020-2100 cumulative oil supply in C1 scenarios



c) CART decision tree for 2020-2100 cumulative gas supply in C1 scenarios

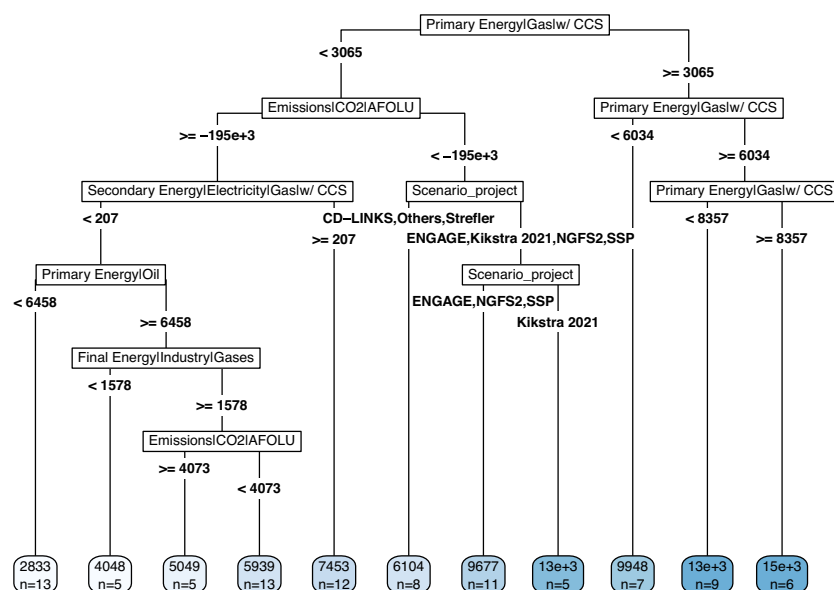


Fig. 2 | Classification and regression tree (CART) analysis results for predicting the 2020–2100 cumulative fossil fuel supply in the C1 scenarios. In panels a–c, the blue boxes at the bottom show the average value of cumulative coal, oil, and gas supply (in exajoules), across the the scenarios included within each given “leaf node” (note that they do not necessarily appear in increasing order from

left to right). The units of the independent variables shown are exajoules for primary and secondary energy, and million tonnes of CO₂ for emissions and carbon sequestration (negative AFOLU emissions represent CO₂ removal). Cumulative 2020–2100 values are also used for the independent variables. (The root mean square errors (RMSE) of panels a–c are, respectively, 233, 734, and 928 EJ).

(Supplementary Fig. 5). Scenarios with relatively higher cumulative gas supply are consistently associated with higher levels of fossil-CCS across the C1–C3 scenarios (Fig. 2c and Supplementary Figs. 10 and 11). For example, six C1 scenarios with the highest cumulative gas supply (around 15,000 EJ) assume that 53%–70% of this supply can be coupled to CCS at the point of combustion. For C3, certain model families and scenario projects are also important predictors (Supplementary Fig. 11).

Since the model family is an important predictor of cumulative fossil fuel supply but is not equally represented in the AR6 ensemble (Supplementary Fig. 3), we test the sensitivity of the median pathways shown in Fig. 1 to potential model bias. There is still limited practice in and consensus on bias correction for model over-/under-representation of climate mitigation scenario ensembles⁴⁰. Nevertheless, when we include only the scenarios with minimum and maximum 2020–2100 cumulative supply from each model family for a given fuel and category, the values and trajectories of the median pathways shown in Fig. 1 do not change much, except for C1-gas in which the post-2050 values would be higher (Supplementary Fig. 12).

Given the substantial variability in modelled gas supply, especially from 2050 onwards, and highly contested debates around the role of gas in energy transitions as previously discussed, we explore the model characteristics and assumptions that underly this variability in more detail in the next section.

Characteristics of scenarios with different roles for gas

We first conduct an analysis of variance (ANOVA) to explore the influence of eight potential drivers of the variability in modelled gas supply over time between 2020–2100 (see Methods). Figure 3 shows that in the C1 scenarios, close to 75% of the variations in the modelled gas supply after 2040 can be explained by differences in the modelling frameworks and scenario designs. Differences in the amounts of fossil-CCS and gas intended for industry use (of which a large fraction goes towards non-energy applications such as for feedstocks, and this variable is also highly correlated with gas demand for transportation) also contribute. In the C2 and C3 scenarios, these four drivers are also the most important, with fossil-CCS becoming the most dominant factor towards the end of the century.

To identify some of the key common underlying dynamics and features of different scenario designs and modelling frameworks that lead to different roles for gas, we next perform a cluster analysis to divide the gas supply pathways into three different typologies according to their modelled values in the years 2030, 2050, 2075, and

2100 (see Methods). As can be seen in Fig. 4 and Supplementary Fig. 13, there are broadly three types of gas trajectories in the C1 and C2 scenarios: (1) rapid decline between now and mid-century followed by a more gradual reduction (“fast decline”); (2) a more gradual decline over time (“slow decline”); and (3) near-term decline followed by an increase in gas supply after around mid-century (“rebound”). In the C3 scenarios (Supplementary Fig. 14), we see the following three types of trajectories: (1) rapid decline between now and mid-century followed by a more gradual reduction (“decline”); (2) near-term decline followed by an increase in gas supply after around mid-century (“rebound”); and (3) increase to around mid-century followed by a plateau (“increase”). For each temperature category, Fig. 4 and Supplementary Figs. 13 and 14 also show the median and interquartile pathways of select model variables in each of the three gas clusters. The model family and scenario project distributions across the gas clusters are shown in Supplementary Figs. 15 and 16.

We summarize key findings across the C1–C3 scenarios here and provide a more detailed discussion in the Supplementary Information. The higher-gas “rebound” and “increase” C1–C3 scenarios are generally associated with one or more of the following features: (1) much higher levels of fossil fuel use coupled to CCS (panel i), including for gas-powered electricity generation (panel t); (2) higher CDR via negative AFOLU emissions (panel l) and DACCS (panel k); (3) lower carbon prices, especially after mid-century (panel n); (4) higher gas demand in the industry and transportation sectors (panels u–v); (5) higher primary energy supply from nuclear (C1 only; panel h); (6) lower capacity additions for electricity generation from solar, wind, and battery storage sources but higher for gas coupled to CCS (panels o–r); (7) lower capital and operation and maintenance costs for electricity generation from gas-CCS power plants in the near-term but higher from offshore wind across all years (panels y, ab, ac, and ae). (For the last two features, we interpret the relevant variables with caution given the relatively limited reporting.) Conversely, the “fast decline” C1–C2 scenarios are typically associated with much less reliance on fossil-CCS, higher carbon prices, and sustained increases in renewable capacity additions from 2020 onwards. The “slow decline” C1–C2 scenarios also share these characteristics, but generally have higher CDR via BECCS and less extremely high carbon prices seen in some of the “fast decline” scenarios. The reduction pathways for gas-powered electricity generation without CCS are, however, similar between the three clusters, showing an almost complete phase-out by around 2040–2060 across the C1–C3 scenarios (panel s).

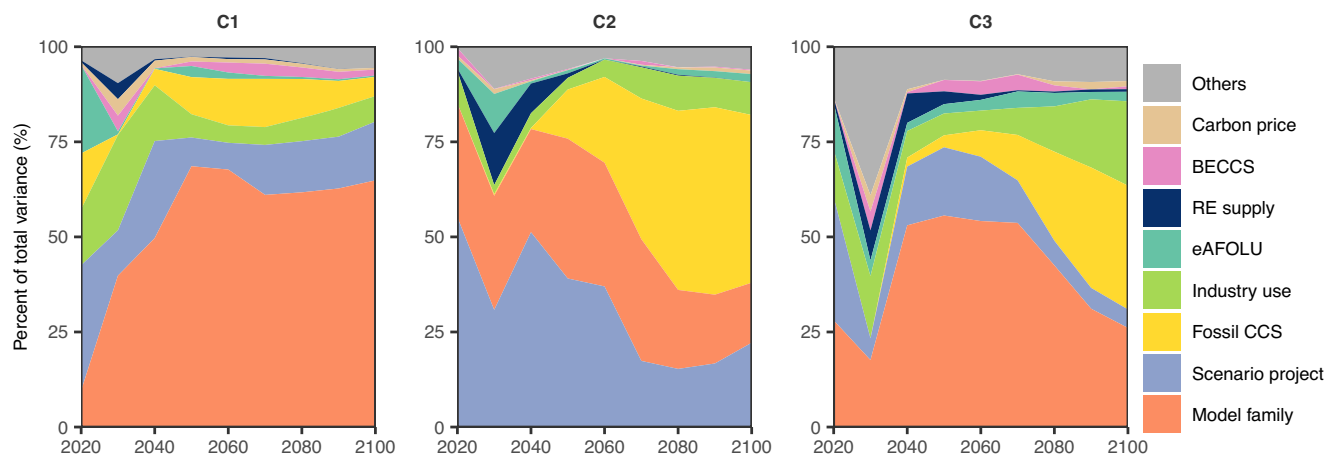


Fig. 3 | Percent contributions of each driver to the variability in modelled gas supply over time between 2020–2100 for the C1–C3 scenarios. A different colour is used for each driver. In each panel, the drivers are ranked in order of decreasing relative contribution across all time, from bottom to top. (“eAFOLU” = CO₂

sequestration by the Agriculture, Forestry, and Other Land Use sector; “RE supply” = primary energy supply from non-biomass renewables; “Others” = remaining, unexplained variance, which can include interactions between the drivers shown.) The “industry use” variable includes both fossil- and bio-based gases.

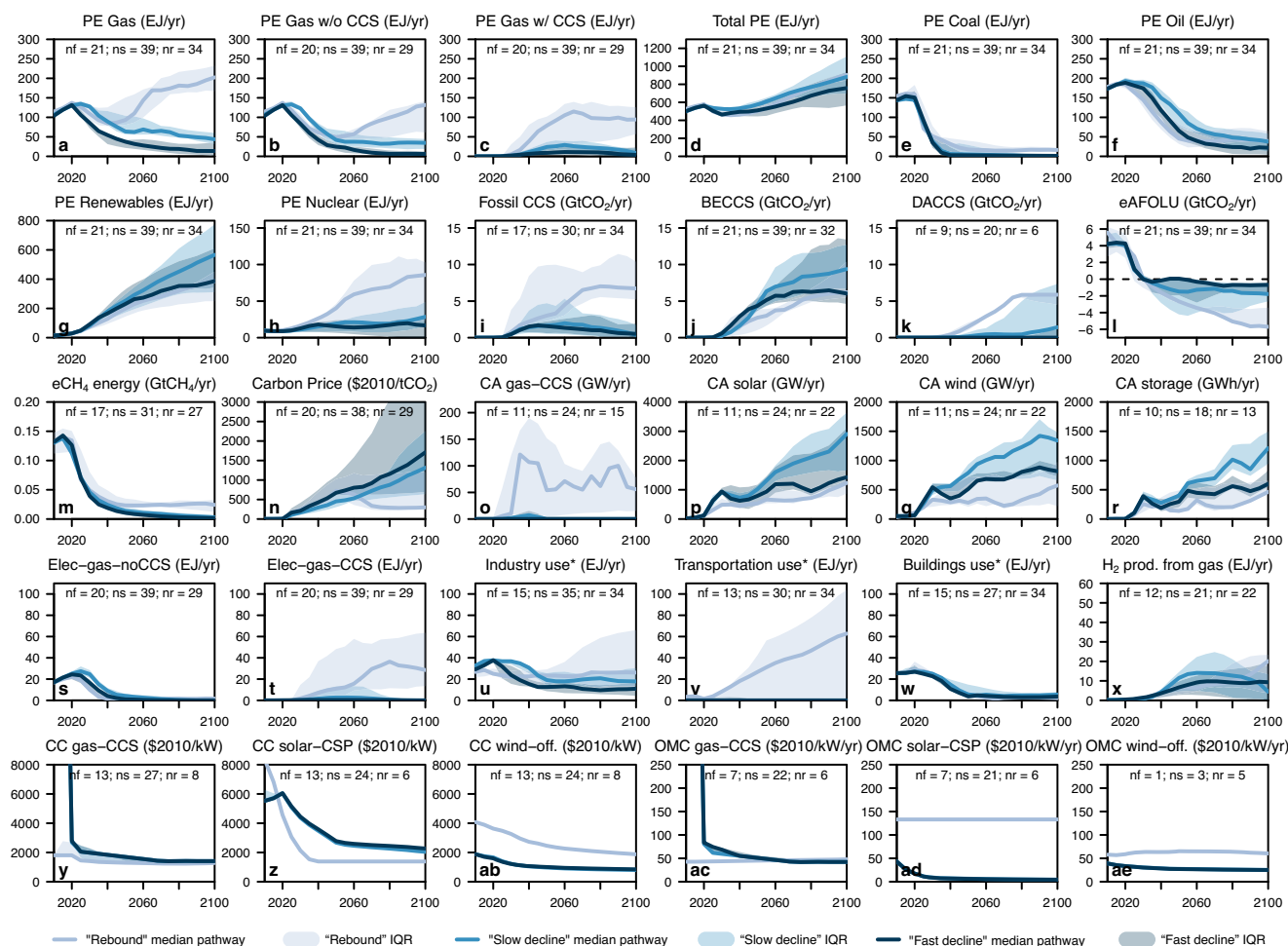


Fig. 4 | 2010–2100 global pathways for select variables as modelled by the C1 scenarios divided into three clusters based on their 2030, 2050, 2075, and 2100 gas supply values. The median (dark lines) pathway and interquartile range (shadings) of each cluster are plotted at 5-year intervals. The variables shown in each panel are as follows: **a** Primary energy from gas; **b, c** Primary energy from gas without and with coupling to carbon capture and storage (CCS); **d** Total primary energy supply; **e–h** Primary energy from coal, oil, non-biomass renewables, and nuclear; **i–k** CCS coupled to fossil fuel use, bioenergy, and direct air capture; **l** Carbon removal and sequestration by the Agriculture, Forestry, and Other Land

Use sector; **m** Methane emissions from the energy sector; **n** Carbon Price; **o–r** Capacity additions to electricity generation from gas with CCS, solar, wind, and battery storage; **s–t** Electricity generation from gas without and with CCS; **u–w** Gas demand (from fossil- and non-fossil sources) for industry, transportation, and buildings; **x** Gas demand for hydrogen production; **y–ae** Capital costs (CC) and operation and maintenance costs (OMC) for gas with CCS, concentrated solar power, and offshore wind for electricity generation. (Notes: Variable units are shown inset; “nx” refers to the number of scenarios within each cluster that outputs a given variable, where x denotes the first letter of the cluster name).

Based on a combination of our ANOVA and gas-cluster analyses, an exploration of individual pathways for different gas clusters grouped by model families (Supplementary Figs. 17–19), and information drawn from the literature on relevant IAM features^{23,24,30,41}, we conclude that the gas trajectories in C1–C3 scenarios are influenced by one or more of the following factors, which are inter-dependent and tend to vary by model family: (1) carbon pricing; (2) constraints on the availability of CCS, CDR, and nuclear technologies; and (3) constraints on renewable deployment (such as assumptions on capital cost, operation and maintenance cost, levelized cost of electricity, and learning rates), resource availability, and integration challenges (e.g., assumptions about flexibility provision, grid expansion, and storage capacity). For example, REMIND has some of the highest carbon prices (Supplementary Fig. 17); imposes the most stringent assumptions on the global and regional CO₂ storage potentials and on the CO₂ injection rate (Supplementary Table 4); and assumes some of the lowest levelized costs of electricity from wind and solar compared to other models (see Fig. 3 in Luderer et al.²⁴). Consequently, all but one C1 scenario from REMIND are grouped into the “fast decline” and “slow decline” clusters, with pathways showing some of the lowest levels of

fossil-CCS (Supplementary Fig. 18), and sustained increases in renewable capacity additions but very limited gas-CCS capacity additions, from 2020 onwards (Supplementary Fig. 19). These findings are consistent with those from Giannousakis et al.⁴¹, who showed that the economics and depths of decarbonization modelled by REMIND are highly sensitive to transport sector costs, CCS injection rate assumptions, and renewable costs.

Conversely, all seven C1 scenarios from IMAGE model high gas supply, generally increasing until around 2060 followed by gradual declines (Supplementary Fig. 17). IMAGE has relatively low carbon prices, no higher than USD₂₀₁₀ 1208 per tonne of CO₂ throughout the century, and imposes no constraints on the regional storage CO₂ potential or the injection rate (Supplementary Table 4). As a result, it models the highest levels of fossil-CCS (> 10 GtCO₂/yr by mid-century) and gas-CCS capacity additions (Supplementary Figs. 18 and 19). Meanwhile, the majority of C1 scenarios from the MESSAGE model family show a gas revival after a near-term decline, displaying some of the highest levels of gas demand for the transport and industry sectors, enabled by high levels of CDR via AFOLU and BECCS and of fossil-CCS. MESSAGE does not impose any constraints on CCS availability

(Supplementary Table 4). This gas revival pattern, also seen in some of the scenarios from the GEM-E3 and WITCH models, may be partly driven by an unexplored but known model outcome associated with the “net-zero-budget” scenario design from the ENGAGE project⁴², in which carbon prices initially increase but then stabilize or decline after net-zero CO₂ emissions are reached around mid-century and mitigation efforts are relaxed (Supplementary Fig. 17; also see Figure SI 1.1-6 in Riahi et al.⁴³).

These differences between higher- and lower-gas scenarios help illustrate the diverging storylines and economics of how the energy transition can unfold to meet climate goals. In many of the higher-gas C1 scenarios, gas use declines rapidly through 2040 (Fig. 4a) but then increases rapidly again through the end of the century to levels far higher than the present. Such scenarios tend to front-load their ambition on oil and gas reductions in the 2030s and 2040s, only to see the deployment of CCS, nuclear energy, and CDR open up room in the carbon budget later in the century (and with corresponding reduced carbon prices) that re-invigorates (in the case of gas power) or newly invigorates (in the case of compressed natural gas-fueled transport vehicles) gas use. By contrast, the “fast decline” scenarios see dramatically faster rates of solar and wind power deployment, with flexible storage capacity that obviates the need for new gas power plants (even with CCS), and helps power the transport sector with more electricity than fossil- or bio-based gases.

How these two scenario typologies would evolve could also have dramatically different real-world implications for the development of technology innovation systems and the accompanying politics⁴³. Nevertheless, given technology path dependencies (a common phenomenon in socioeconomic systems, which arises when initial conditions and their historical antecedents matter for eventual outcomes)⁴⁴, combined with the urgent need to rapidly decarbonize our energy systems, a gas phase-down followed by a revival seems questionable and calls for a careful justification that we could not find in the underlying studies. Due to the high heterogeneity in and limited transparency around IAM assumptions, combined with inconsistencies in variable reporting, we could not determine which model parameters and assumptions are specifically leading to this outcome. We offer three most likely possible explanations: (1) inadequate model representation of real-world constraints on fossil fuel- and renewable-based technology innovation, adoption, diffusion, and phase-in/-out path dependencies^{44,45} (for example, an overestimation of the costs of renewable technologies is a problem that has been found in many IAMs^{46,47} and which leads to higher mitigation value of CCS in electricity and hydrogen production⁴⁸); (2) overly optimistic assumptions or insufficient constraints on CCS and CDR potential (for example, only the REMIND model imposes constraints on the regional CO₂ storage potential and injection rate, which influence fossil-CCS, BECCS, and DACCS availability)^{30,49}; and, in the case of “net-zero-budget” scenarios specifically, (3) an unexplored but known model outcome in which carbon prices and mitigation efforts are relaxed after net-zero CO₂ emissions are reached in some of the models. In light of the important policy implications, we urge the model-scenario developers to more consistently report key model parameters, assumptions, and outputs, and to critically examine the real-world implications of their modelled results for gas pathways.

Sensitivity of global fossil fuel reduction pathways to different mitigation strategies and uncertainties in CDR potential

To further assess and demonstrate how much the reduction pathways of coal, oil, and gas are influenced by different scenario storylines and assumptions, in this section, we first focus on a number of individual illustrative scenarios and then explore what happens when we take a conservative approach to future CDR and fossil-CCS potential. The AR6 scenarios database identified five different “illustrative mitigation pathways” (IMPs) that reflect different prominent mitigation strategies

for reaching a given temperature outcome (see Fig. 5 legend). We emphasize that no two scenarios are alike or more “correct” than others; the IMPs are not representative of the AR6 ensemble. The individual coal, oil, and gas supply pathways under the five IMPs, along with the median pathways across each of the C1-C3 scenarios, are shown in Fig. 5. (Other select model variables from these pathways are also shown in Supplementary Figs. 20–22) We describe the fossil fuel decline pathways under the five IMPs in detail in the Supplementary Information, and highlight some key features of the IMP-LD, -SP, and -Neg scenarios here.

In the C1 category, the IMP-LD (low-energy demand) scenario charts out much faster reductions in oil and gas than almost all other scenarios (Fig. 5b, c). For oil, this is accomplished through widespread transitions to shared vehicle fleets, flexible transit systems, and rapid vehicle electrification, as well as reductions in freight volumes due to longer-lasting and more material-efficient goods. For gas, this is accomplished through extensive end-use efficiency improvements (e.g., through building retrofits), plus preferring renewable power to gas with CCS. In fact, the IMP-LD scenario deploys no fossil-CCS or BECCS for normative reasons, informed by concern over innovation failure, investment risks, and public opposition (though it does rely extensively on CDR via AFOLU; see Supplementary Fig. 20)⁵⁰.

In contrast, the IMP-SP's explicit focus on increasing access to affordable modern energy services (e.g., electric and LPG cook stoves) in developing regions causes it to reduce oil and gas demand slightly slower than the IMP-LD. IMP-SP subsequently phases out all fossil fuels almost completely by the end of the century and with relatively limited CDR and CCS reliance (Supplementary Fig. 20), driven in part by the “substantially reduce[d] detrimental effects of outdoor air pollution on public health”, and by the potential negative environmental and social impacts of intensive land use-based CDR⁵¹.

In the C2 category, the IMP-Neg scenario allows dramatically more room for coal than most scenarios but, over time, less room for gas (Fig. 5). The continued use of coal in this scenario is driven by industry demand, which is enabled by coupling to CCS and also by extensive CDR reliance: up to 8 GtCO₂ of BECCS, 1–2 GtCO₂ of sequestration by the AFOLU sector, and 6 GtCO₂ by other sequestration methods annually in the latter half of the century⁴² (Supplementary Fig. 21). This extensive reliance on long-term CDR is typical of C2 scenarios, in which net negative CO₂ emissions are needed to compensate for emissions in the first half of the century and bring down temperatures after the peak²¹.

Figure 5 also shows the median and interquartile ranges of C1–C3 pathways constrained by the potential 2020–2100 cumulative availability of BECCS (196 GtCO₂), afforestation (224 GtCO₂), and DACCS (320 GtCO₂) based on a recent expert consensus survey⁴⁹. We find that 15%, 0%, and 10% of the C1, C2, and C3 scenarios, respectively, are within these limits (not all scenarios report the variables needed for this analysis; see Methods for details). The selected scenarios also have levels of total CCS (coupled to fossil fuel use, bioenergy use, and direct air capture) below 8.6 GtCO₂ per year around mid-century, which is the “investable” CO₂ storage capacity estimated by Grant et al.³⁰ after accounting for real-world regional differences in storage capacity and injection rates. Imposing these CDR limits implies much faster and greater reductions in fossil fuel supply and use compared to the full AR6 ensemble, especially for gas, in the near- and long-term. As Fig. 5 shows, the resulting median coal, oil, and gas reduction pathways fall around or below the 25th percentile of all scenarios. For example, under the median pathway calculated from all C1 scenarios, global coal, oil, and gas supply declined by 95%, 62%, and 42%, respectively, between 2020 and 2050. Under the median pathway of the CDR-limited scenarios, the respective declines are 99%, 70%, and 84% (see Supplementary Tables 1, 2 for details).

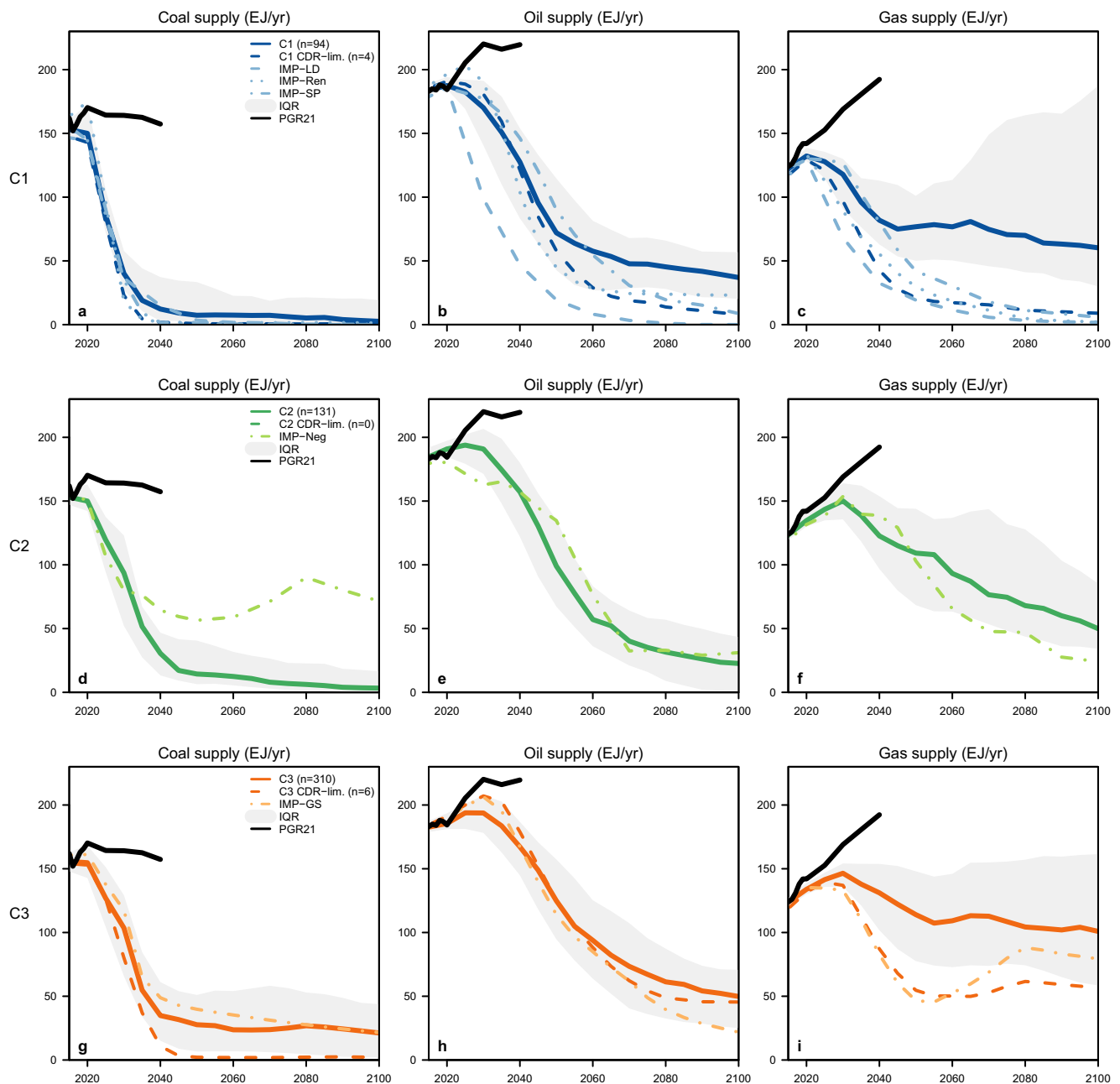


Fig. 5 | 2015–2100 global pathways of fossil fuel supply under different individual or subsets of AR6-assessed scenarios and compared to those based on government plans and projections. Panels a–i show global pathways of primary energy supply (in exajoules, EJ) from coal, oil, and gas under different subsets of or individual C1–C3 pathways as denoted inset: (1) the median pathway (solid lines) and interquartile ranges (IQRs, grey shadings) of all scenarios (“n” denotes the number of scenarios); (2) the median pathway of scenarios constrained by cumulative BECCS, afforestation, and DACCS limits based on expert consensus of their future CDR potential⁴⁹ (“CDR-lim.”); and (3) individual AR6 illustrative

mitigation pathways: “IMP-LD” – strong emphasis on energy demand reductions; “IMP-Ren” – heavy reliance on renewables; “IMP-SP” – mitigation in the context of broader sustainable development; “IMP-Neg” – extensive CDR in the energy and the industry sectors; and “IMP-GS” – less rapid and gradual strengthening of near-term mitigation actions. The projected levels of supply based on government plans and projections are shown by the black lines (“PGR21”), as estimated in the 2021 Production Gap Report⁵. See Supplementary Table 1 for the percentage reductions in coal, oil, gas supply relative to 2020 under all pathways shown.

Our findings thus highlight the tug-of-war over the fate of fossil fuels. Pulling strongly towards a rapid reduction are policies and actions that avoid and reduce emissions. Pulling the other way – or, at least, moderating the decline – is CDR and CCS, allowing for the continued use of fossil fuels, especially gas. These different approaches, while complementary and necessary from the perspective of increasing our chances of holding warming to within the Paris Agreement’s temperature limits, nonetheless raises questions about which pathways may be more desirable with respect to other important societal

and environmental outcomes, more precautionary with respect to safeguarding public and planetary health, and/or more feasible to attain^{14,52–54}.

Although researchers are only beginning to grapple with these questions, individual AR6 scenarios have been evaluated in terms of feasibility along five dimensions: geophysical, economic, technological, socio-cultural, and institutional²¹. Figure 6 shows the feasibility assessments of the pathways plotted in Fig. 5 (see Methods). We draw three main insights from this evaluation. First, all AR6 C1–C3 pathways

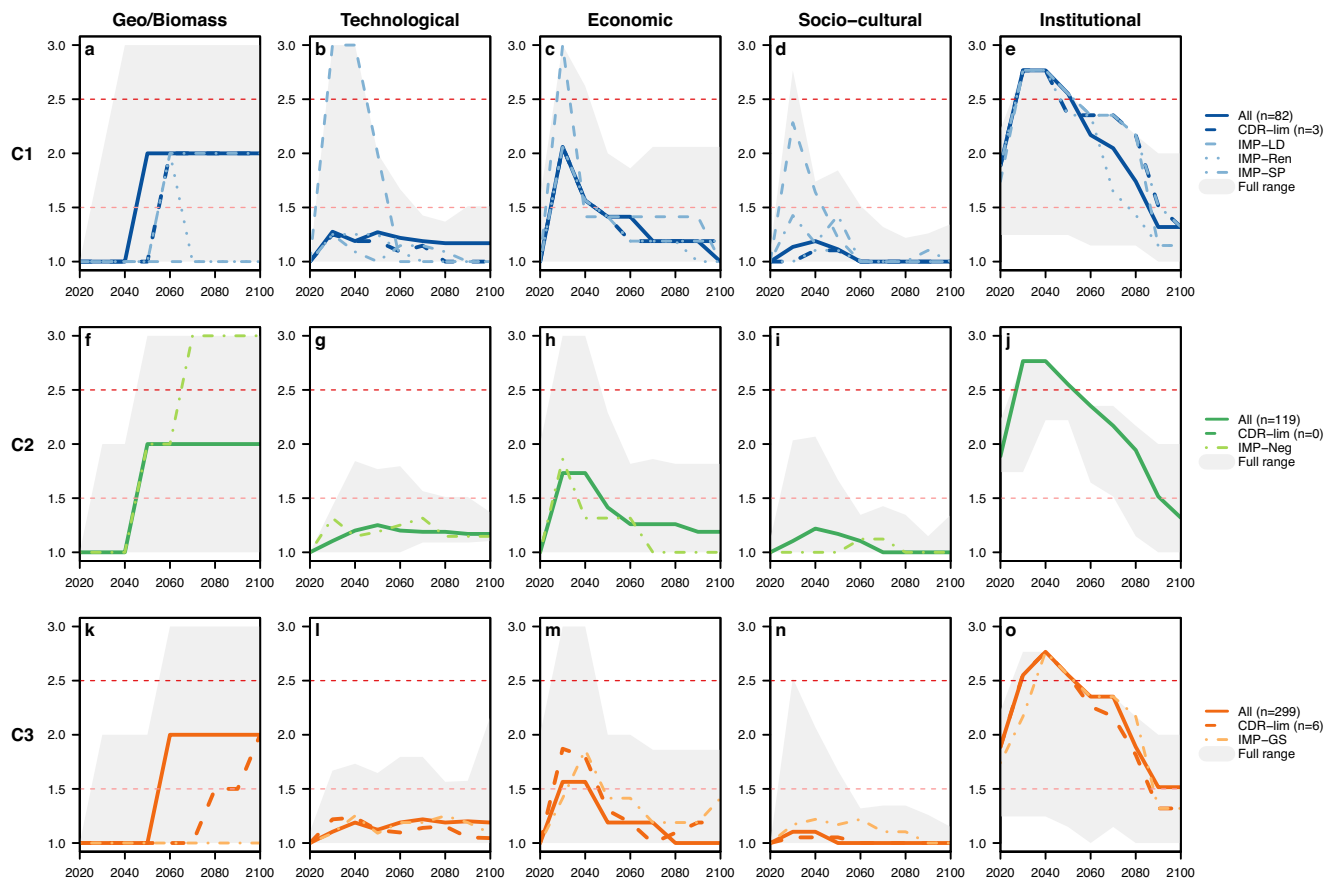


Fig. 6 | Feasibility assessment by the IPCC AR6 WGIII of the C1–C3 pathways across five different dimensions. Panels a–o show the 2020–2100 decadal feasibility assessment ratings by the IPCC AR6 WGIII of the C1–C3 pathways shown in Fig. 5. The grey shadings represent the full ranges of values across each of the C1–C3 ensembles. The feasibility ratings are as follows: Less than 1.5 = Low/

Plausible; >1.5–2.5 = Medium / Best case scenario; More than 2.5 = High / Unprecedented. Following Figure 3.43 of the IPCC AR6 WGIII Chapter 3, the geophysical feasibility dimension shown here is for the biomass potential indicator only. (“n” denotes the number of scenarios with available data; no data are available for assessing the institutional feasibility dimension of the C2 IMP-Neg.).

face “unprecedented” challenges in terms of governance if the continuation of current trends and existing capacities are assumed. In particular, the IMP-SP may require even greater institutional breakthroughs and coordination to ensure an equitable transition away from fossil fuels.

Second, pathways that pursue more stringent temperature outcomes are generally associated with more disruptive transformations in the near-term but then present fewer feasibility challenges and risks later. For example, among the C1 IMPs, the LD scenario, which phases out fossil fuels the fastest through substantial energy demand reductions, is associated with the highest technological, economic, and socio-cultural feasibility concerns in the near-term. In the long run, however, it presents an opportunity to avoid risks associated with delayed mitigation and reliance on uncertain CDR technologies.

Third, pathways that delay climate action and rely on extensive CDR (and consequently allow for a more gradual transition away from fossil fuels) are associated with fewer near-term technological, economic, and socio-cultural feasibility concerns, but present “unprecedented” geophysical feasibility concerns in the long-run due to how much land would be required to sustain the levels of negative emissions assumed to occur via BECCS (this is the only CDR method evaluated in the AR6 feasibility assessment). Moreover, as stated previously, only 0–15% of the C1–C3 scenarios rely on future levels of BECCS, AR, and/or DACCS below the potential cumulative limits estimated by some experts.

Discussion

In 2021, governments reaffirmed their commitment to strive to limit global warming to 1.5 °C in the Glasgow Climate Pact¹. Our analysis finds that there is a strong consensus in the AR6-assessed scenarios that global supply and demand of coal, oil, and gas need to decline substantially and rapidly between now and 2050 to limit warming to 1.5 °C with no or limited overshoot, and even more so if fossil-CCS and CDR technologies fail to develop at scale (i.e., by 99% for coal, 70% for oil, and 84% for gas). A recent paper estimates that, since the AR6-assessed scenarios were compiled, the remaining carbon budget for a 50% chance of limiting long-term warming to 1.5 °C has likely shrunk by 50% and now stands at 250 GtCO₂⁵⁵, which would necessitate even more ambitious near-term mitigation efforts across all sectors.

Many world governments seem to increasingly acknowledge the need to reduce fossil fuel demand, expand clean energy alternatives, and minimize methane emissions along the oil and gas supply chain as key climate mitigation strategies, as evidenced by the Glasgow Climate Pact’s mention of moving away from (unabated) coal use and the US government’s Inflation Reduction Act’s focus on boosting solar and wind capacity, for example. When it comes to fossil fuel supply, however, governments’ plans and projections remain vastly misaligned with pathways consistent with limiting warming to 1.5 °C or 2 °C, with estimates as of 2021⁶ showing only modest decreases in coal and increasing oil and gas supply out to at least 2040 (Fig. 5, black lines), creating vast so-called “production gaps”. For example, compared to the median pathway modelled by all AR6-assessed C1 scenarios, global

production levels derived from governments' energy outlooks would lead to 1200% (145 EJ) more coal, 72% (92 EJ) more oil, and 135% (110 EJ) more gas in 2040. Under the CDR-limited C1 pathways, the respective production gaps increase to 8600% (156 EJ) for coal, 81% (98 EJ) for oil, and 350% (150 EJ) for gas.

Consequently, the first policy implication of our analysis is that governments could better align their climate and energy policies by planning for and implementing an active transition away from coal, oil, and gas production along with use, starting now. Only a few fossil fuel-producing countries have begun to consider the alignment of their production and export targets with national and international climate goals, and many continue to subsidize, invest in, and plan on expanding production. This disconnect perpetuates the “production gap”, undermining the Paris Agreement's long-term temperature goal and creating risks of stranded communities and assets⁶. Additionally, prior studies have shown that, to keep within the carbon budget for limiting warming to 1.5 °C with a 50% likelihood, 90% of coal and 60% of oil and gas must remain unextracted⁵⁶, while projected CO₂ emissions from existing fossil-fuel-production or -combustion infrastructure without additional abatement would already exceed this budget^{57,58}. Combining policies to limit fossil fuel supply with policies to limit demand reduces the overall cost of achieving emission reduction goals, promotes policy coherence, helps to ensure that renewable deployment will lead to an energy transition as opposed to an addition, and directly challenges public and private vested interests who continue to lock in high fossil fuel dependence^{59–64}. Furthermore, planning for and implementing a managed and equitable transition with international cooperation can help to ensure a fairer distribution of the shrinking carbon budget^{65,66} and to minimize disruption for fossil fuel-dependent communities and workers⁶⁷.

Secondly, other mitigation options – such as minimizing methane emissions from fossil fuel production processes – are important but are not a substitute for directly reducing fossil fuel supply itself, which must also occur in tandem (see panel m in Fig. 4 and Supplementary Figs. 13, 14, 20–22). Some major producers – the US, Canada, Norway, Qatar, and Saudi Arabi – established the Net-Zero Producers Forum in 2021 (the UAE joined in 2022), with goals to develop mitigation strategies ranging from methane abatement to development of clean-energy and CCS technologies, but did not mention the need to reduce oil and gas production⁶⁸. Proponents of natural gas are using the “bridge”, “transition”, or “cleaner” fuel narrative to justify and legitimize support and investment for expanding extraction and consumption infrastructure. However, gas could hinder or delay renewable energy transitions through locking-in fossil fuel-based technological systems and related institutions, and has been found to offer smaller benefits as an alternative to coal in terms of minimizing GHG emissions and climate impacts than originally estimated after accounting for methane leakage along the gas supply chain, which may not yet be adequately captured in existing IAMs¹⁴. Our analysis finds that the AR6-assessed scenarios that limit warming to 1.5 °C with no or limited overshoot and that model long-term high gas reliance are contingent upon high fossil-CCS and CDR deployment, and are most likely driven by inadequate representation of real-world constraints on CO₂ storage potential and on fossil fuel- and renewable-based technology innovation, adoption, diffusion, and phase-in/-out path dependencies in certain model frameworks and scenario designs. We thus conclude that our analysis lends support for the replacement of the bridge narrative, as proposed by Kemfert et al.¹⁴, with unambiguous near- and long-term reduction benchmarks for gas production and use (e.g., by 84% between now and 2050).

Finally, the pace and extent of the required global coal, oil, and gas reduction pathways (and their relative differences) will depend on many normative factors and value-laden policy choices, some of which cannot be adequately informed by IAMs alone⁶⁹. For example, what is the level of risk society is willing to accept in terms of the probability of

limiting long-term warming to 1.5 °C? To what extent should we assume that future CDR and CCS can be developed and deployed at scale? Which climate mitigation strategy might be the most feasible and/or the most desirable? Countries' differentiated capacities and circumstances, and other equity principles, should also be considered when disaggregating global coal, oil, gas reduction benchmarks – and their relative contributions – into national pathways^{70–72}. Existing low-carbon scenarios, including those analysed here, rarely incorporate equity and environmental justice considerations and are primarily driven by cost optimization³¹. For example, the rates of coal phase-out modelled by IAMs have been found to be much faster than historical precedents and would place the burden of stranded assets disproportionately on lower-income countries; greater emissions reductions in higher-income countries and faster reductions in global oil and gas could allow for a slightly slower coal phase-out in lower-income countries^{73,74}.

As many others have argued^{26,49,54,75,76}, taking a precautionary approach to minimizing climate damages would suggest opting for the most stringent temperature outcome – as reaffirmed by governments worldwide in the 2021 Glasgow Climate Pact¹ – and following pathways that limit their reliance on uncertain technologies, given that IAMs do not reflect the risk of failure of the technologies or measures on which they rely. Global rates of CCS deployment continue to fall below expectations and remain far below those modelled in the mitigation scenarios, with a total annual capacity of 45 MtCO₂ as of 2021^{31,77}. IAMs generally assume that CO₂ storage is a low-cost and globally ubiquitous resource; however, Grant et al. showed that this may lead models to substantially overestimate the role of CCS (coupled to fossil fuel and bioenergy use and/or direct air capture) – while under-utilizing renewable deployment – for decarbonization, when accounting for the technical, financial, and institutional barriers that may impose practicable limits on regional injection rates³⁰. A climate mitigation strategy that entails a fossil fuel phase-out with limited CDR and CCS reliance would also bring about localized, near-term benefits from reduced air and water pollution^{78,79}, human rights violations⁸⁰, and biodiversity loss⁸¹, among others. For example, exposure to outdoor fine particulate matter pollution from fossil fuel combustion is estimated to lead to around 8.7 million premature deaths worldwide each year⁸², while an increasing number of studies are documenting adverse health impacts including premature birth, respiratory diseases, and cancer associated with living near fossil fuel extraction sites^{83–86}.

Nevertheless, aiming to limit warming to 1.5 °C with no or limited overshoot with minimal reliance on future CDR and CCS will entail some technological, economic, and socio-cultural feasibility challenges in the near-term, as this mitigation strategy implies rapid and substantial energy demand reductions, electrification and deployment of clean energy, and lifestyle shifts. But, as the IPCC notes, “feasibility concerns are context and time-dependent and malleable: enabling conditions can help overcome them”²¹. For example, rapid deployment of low-carbon technology in the near-term can help to lower the barriers for future government policy and ensure the political durability of decarbonization, as actors increasingly buy into new technologies, creating positive feedback cycles and building new low-carbon labour forces^{57,88}, even if actions to side-line entrenched interests and associated predatory delay will still be required^{62,89}. Moreover, all scenarios that limit warming to 2 °C or below come with “unprecedented” feasibility concerns, especially in terms of institutional capacity, beyond what the IPCC could identify as plausible “best case” examples from history. Increasing international cooperation and improving the capacities of individual governments and other institutions to implement ambitious climate policies will be essential, especially for a global transition away from fossil fuels to occur in a managed and equitable manner^{70,90}.

While the scenarios assessed in the IPCC AR6 offer a wealth of information in terms of strategies for decarbonizing our energy

systems, it is important for decision-makers to understand their limitations and shortcomings, and the associated risks and ethical concerns of different modelled pathways, including the potential failure of CDR and CCS technologies to develop at scale^{75,91}, when using them to inform global and national climate policy agendas. The scenarios' differentiated alignment with other important societal and environmental outcomes like the Sustainable Development Goals (SDGs), equity, and other lines of evidence should also be evaluated⁹². Understanding the feasibility concerns of different scenarios can provide a valuable tool for identifying enabling conditions that can help to overcome them⁵². We also note that our analysis reflects only the possibilities explored in the studies underlying the AR6 scenario ensemble. Other researchers have, for example, modelled alternative degrowth scenarios in which continued growth in gross domestic production is not a prerequisite to support societal wellbeing, finding that such mitigation scenarios minimize many key feasibility and sustainability risks compared to technology-driven pathways⁹³.

Methods

The IPCC AR6 WGIII scenarios database

The raw data and metadata from all models and scenarios were downloaded from the IPCC AR6 WGIII Scenarios Database (release 1.1) hosted by the International Institute for Applied Systems Analysis⁹⁴. Although the “IMP-Neg” scenario (“EN_NPi2020_400f_lowBECC”) from the COFFEE 1.1 model is technically categorized as a C3 in the database, we categorize it as a C2 scenario here, following the IPCC AR6 WGIII Chapter 3, Table 3.2 (i.e., “The warming profile of Neg peaks around 2060 and declines to below 1.5 °C (50% likelihood) shortly after 2100. Whilst technically classified as a C3, it strongly exhibits the characteristics of C2 high overshoot scenarios”). Model outputs are available at 5- or 10-year intervals; for the latter, linear interpolation is applied to derive values at 5-year intervals for all scenarios. For all variables analysed, we estimate the cumulative 2020–2100 values from annual values derived by linear interpolation. Because the AR6 scenario ensemble is unstructured, the number of scenarios displaying a given pattern does not reflect an increased likelihood of that specific outcome. The averages and ranges of results merely reflect the options that have been explored in the studies that produced the scenarios.

Global fossil fuel supply values are taken from the “Primary Energy|Coal”, “Primary Energy|Oil”, and “Primary Energy|Gas” variables, which are provided in units of exajoules (EJ) per year, and reported by 97–100% of the C1–C3 scenarios (Supplementary Table 3). According to our knowledge of the COFFEE model and a 2013 survey ran by the International Institute for Applied Systems Analysis (IIASA) (V. Krey, IIASA, personal communication to R. Schaeffer, October 27, 2019), 10 of the 11 model families whose scenarios (534 out of 535 scenarios) are analysed in this paper include non-energy use under their reporting of “Primary Energy|xx”: AIM, COFFEE, GCAM, GEM-E3, IMAGE, MESSAGE, POLES, REMIND, TIAM, and WITCH. (We do not know whether the EPPA model accounts for non-energy use, but there is only one C3 scenario from EPPA analysed here.) Thus, here we broadly interpret the “Primary Energy|xx” variable to represent total fossil fuel supply for all intended uses (i.e., combustion and non-combustion uses, such as for chemical or plastics feedstocks). However, the level of detail to which non-combustion uses are accounted for likely varies between different models. More consistent documentation and reporting of this issue, including by the “Final Energy|Non-Energy Use|xx” output variables (currently reported by 32–58% of the C1–C3 scenarios), would aid our analysis and interpretation. In trying to subsequently analyse which demand sectors may be heavily influencing modelled fossil fuel supply, we try to account for non-energy uses to the extent possible, using the more completely reported variable “Final Energy|Industry|xx” (where xx = Solids, Liquids, or Gases; reported by 87–93%), although this variable can include non-

fossil fuel sources. Supplementary Figs. 23 and 24 show the individual, median, and interquartile range (IQR) 2010–2100 pathways, as well as boxplot distributions of the cumulative 2020–2100 values, of the “Final Energy|Non-Energy Use|xx” and “Final Energy|Industry|xx” variables, respectively, as modelled by the C1–C3 scenarios.

Classification and regression tree analysis (CART)

CART is a commonly used algorithm for identifying groups of scenarios by a sequence of classification rules³⁸. CART can statistically demonstrate which factors are particularly important in a model or relationship in terms of explanatory power and variance while presenting the data in a way that is easily interpreted by those not well-versed in statistical analysis. We performed a CART analysis to identify the combinations of characteristics and features that are most predictive of the modelled levels of cumulative 2020–2100 supply of coal, oil, or gas in each temperature category (C1–C3 scenarios); the results are shown in Fig. 2 and Supplementary Figs. 6–11. We implemented our CART modelling using the R package *rpart*⁹⁵. CART analysis consists of finding splits of the independent continuous or categorical variables that yield the strongest possible predictions of a dependent variable. Independent variables are not required to follow any specific distribution, and nonlinear relationships as well as interaction effects are readily captured³⁸.

The independent categorical and continuous variables we chose to include in our analysis reflect those that are frequently discussed in the literature^{21,23,39} and/or judged to likely influence the level of fossil fuel dependence and are reported by more than two-thirds of the model-scenarios. These fall under five broad categories as follows: 1) Total primary energy supply and primary energy supply from alternative sources, including other fossil fuels; 2) End-use by different sectors (for industry use, the available variable accounts for non-energy uses but includes both fossil fuel- and bio-based sources); 3) Technologies that would enable more or less fossil fuel use, including CDR and CCS; 4) Carbon pricing – a general indicator of policy stringency and disruptiveness in the IAMs⁴²; and 5) Model family and scenario project. Given a large number of individual project studies in the AR6 ensemble, the latter variable is created from the “Project_study” metadata variable by grouping projects with a relatively small number of scenarios (Supplementary Fig. 3) into one “Others” category. We use this as a proxy for capturing broad differences in scenario design but note that differences can also exist within a large project, such as ENGAGE which specifically compares net-zero budget against end-of-century budget designs⁴². For ease of interpretation and readability, we limited the tree growth by pruning the tree using *k*-fold cross-validation and limiting the minimum number of scenarios in a leaf node to 5% of the total in each category. Following general convention, we used a value of *k* = 10 and selected the simplest tree within one standard error of the best tree (lowest cross-validated relative error)⁹⁶.

Analysis of variance (ANOVA) and K-means clustering

To identify the factors that contribute most to the variability in modelled gas supply between 2020 and 2100 in each of the C1–C3 scenario ensemble, we performed an analysis of variance (ANOVA), following Guivarch and Monjon (2017)⁹⁷. The contributions of each driver over time is based on the partitioning of the sum of squares in a linear regression. The total sum of squares (i.e. the variance of the results, multiplied by the number of scenarios minus one) can be partitioned into the explained sum of squares linked to each uncertainty driver and the residual sum of squares. This partitioning of the sum of squares is computed at each decadal interval for the ensemble of scenarios. It gives the fraction of variance explained by each uncertainty driver at each time step. To minimize multi-collinearity between the independent variables, we include only eight categorical and continuous independent variables identified as most important in our CART analysis: “Model family”, “Scenario project”, “Carbon Sequestration|CCS|

Biomass”, “Carbon Sequestration|CCS|Fossil”, “Emissions|CO₂|AFOLU”, “Final Energy|Industry|Gases” (which is highly correlated with “Final Energy|Transportation|Gases”), “Price|Carbon”, and “Primary Energy|Non-Biomass Renewables”. The Variance Inflation Factor in our ANOVA models for all fuels, categories, and years did not exceed 3.1. (These final energy variables include both fossil fuel- and bio-based sources.)

We use the R package *cluster* to group the scenarios in each of the C1–C3 categories into three different types based on their modelled values of gas supply in 2030, 2050, 2075, and 2100 by *k*-means clustering⁹⁸. This is one of the most commonly used unsupervised machine learning algorithm for partitioning a given data set into groups, where *k* represents the number of groups pre-specified. It classifies objects in multiple groups (i.e., clusters), such that objects within the same cluster are as similar as possible, whereas objects from different clusters are as dissimilar as possible. Based on Fig. 1, we observe three general patterns of gas supply trajectories in each of the C1–C3 categories and therefore chose a value of *k* = 3.

Sensitivity analysis to uncertainties in CDR potential

In Fig. 3, we limited the CDR levels that a scenario can rely on based on the median cumulative 2020–2100 feasible potential derived from an expert consensus survey conducted by Grant et al.⁴⁹ for three CDR methods: no more than 196, 224, and 320 GtCO₂ of BECCS, afforestation, and DACCS, respectively. This feasible potential reflects a combination of technical constraints (e.g., resource availability in terms of how much biomass can be grown for energy⁹⁹), sustainability considerations (e.g., intensive land use for bioenergy or CO₂ sequestration by the AFOLU sector could lead to land degradation, food insecurity, biodiversity loss, and water scarcity^{28,29}), as well as social and governance concerns⁴⁹.

We use the values reported under the “Carbon Sequestration|CCS|Biomass” variable (reported by 93–98% across the C1–C3 scenarios) to constrain BECCS and “Carbon Sequestration|Direct Air Capture” to constrain DACCS (reported by 25–41%). Given that 62–66% of the scenarios report “Carbon Sequestration|Land Use” and 39–55% report “Carbon Sequestration|Land Use|Afforestation”, we use the former variable representing total sequestration by all land use methods when the latter is not available to increase the coverage for constraining afforestation. The resulting median pathways of coal, oil, and gas supply are not affected by applying this proxy method compared to using the “Carbon Sequestration|Land Use|Afforestation” variable alone (see Supplementary Fig. 25). If a model-scenario reports zero for a particular variable, we assume that CDR method is modelled and the output is zero. If the variable is not reported, we exclude that model-scenario from the CDR-limited subset given that CDR may still be used at levels exceeding the thresholds. For example, all model-scenarios report net AFOLU emissions, but only 39–55% report afforestation under the “Carbon Sequestration|Land Use|Afforestation” variable, meaning that some models implicitly rely on afforestation but do not report it. Given this lack of reporting consistency, especially for land use sequestration, some errors may have been introduced in our interpretation.

The median values (and interquartile ranges) of cumulative 2020–2100 CDR via BECCS, afforestation, and DACCS in the C1–C3 scenarios are 328 (253–527) GtCO₂, 217 (136–240) GtCO₂, and 29 (0–192) GtCO₂, respectively (see Table 3.5 of the AR6 WGIII Chapter 3 for details²¹). We find that 4 out of 26 C1, 0 out of 16 C2, and 6 out of 62 C3 scenarios that report the relevant variables do not exceed the limits based on Grant et al.⁴⁹.

Feasibility assessment of the mitigation scenarios

The IPCC AR6 WGIII assessed the feasibility of mitigation scenarios along five dimensions: geophysical, technological, economic,

institutional, and socio-cultural, following the methods developed by Brutschin et al.⁵². Table II.1 of the IPCC AR6 WGIII Annex III summarizes the indicators used for each dimension, and their respective thresholds for the categorization of values exceeding medium or high levels of concern¹⁰⁰. For a given indicator, a rating of 1–3 is assigned as follows: below the medium threshold value = 1; between the medium and high threshold values = 2; and above the high threshold value = 3. For a given feasibility dimension, the relevant indicator ratings are then aggregated using the geometric mean, with the resulting mean categorized as follows: <1.5 = “plausible”; 1.5–2.5 = “best case”; and >2.5 = “unprecedented”.

Data limitations

In general, our analyses and scenario interpretations are constrained by data availability: not all variables are consistently reported across the AR6 model-scenarios (Supplementary Table 3). Consequently, there could be a model sample bias in the median and distributions shown for a given variable, or in the independent variables identified as the most important predictors in the CART and ANOVA analyses. Increased transparency and reporting of model inputs, parameters, assumptions, and outputs, such as on the costs of different energy technologies, carbon prices, the levels and specific methods of CDR assumed, and differentiated fossil fuel end-uses by sector, across all IAMs would increase their interpretability for policy analysis.

Data availability

All raw data and metadata of the scenarios analysed in this study were downloaded from the IPCC AR6 Scenarios Database (release 1.1) hosted by the International Institute for Applied Systems Analysis, available at: <https://data.ece.iiasa.ac.at/ar6/>. Data on the feasibility assessments of the C1–C3 scenarios used in this study, and all data generated in this study, can be downloaded from <https://github.com/pjoy-a/NCOMMS-AR6-FF>.

Code availability

Scripts to generate the analyses and figures in the manuscript are available from <https://github.com/pjoy-a/NCOMMS-AR6-FF>.

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Author contributions

P.A. led the analysis and manuscript preparation with help from P.E., P.A., P.E., C.G., R.S., and S.P. designed the paper concept. E.B. generated and provided data on the feasibility assessment of the IPCC AR6 scenarios database. All authors contributed to the text.

Competing interests

The authors declare no competing interests.

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Correspondence and requests for materials should be addressed to Ploy Achakulwisut.

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Uncertainties, Costs, and Bottlenecks of Large-Scale Direct Air Capture of CO₂

Leonardo Chiani^{1,2,3*}, Pietro Andreoni^{1,2,3}, Laurent Drouet^{2,3},
Katrin Sievert^{4,5}, Tobias Schmidt⁵, Bjarne Steffen^{4,5,6},
Massimo Tavoni^{1,2,3}

^{1*} Department of Management Engineering, Politecnico di Milano, Italy.

² CMCC Foundation - Euro-Mediterranean Center on Climate Change, Italy.

³ RFF-CMCC European Institute on Economics and the Environment, Italy.

⁴ Climate Finance and Policy Group, ETH Zurich, Switzerland.

⁵ Energy and Technology Policy Group, ETH Zurich, Switzerland.

⁶ Center for Energy and Environmental Policy Research, Massachusetts Institute of Technology, USA.

Contributing authors: leonardo.chiani@polimi.it;

Abstract

Direct air carbon capture and storage (DACCS) is a promising CO₂ removal technology, but its deployment at scale remains speculative. Yet, its technological, economic, and policy-related uncertainties have often been overlooked in mitigation pathways. This paper conducts the first uncertainty quantification and global sensitivity analysis of DACCS through a detailed-process Integrated Assessment Model and recently developed sensitivity indexes. We observe a fat-tailed distribution in the potential deployment of DACCS, meaning that while most outcomes show modest uptake levels, there remains a small but non-negligible probability (4–6%) of achieving gigaton-scale removals by mid-century. For weak climate targets, scaling DACCS to gigaton levels requires massive global subsidies, up to 3 [95% confidence interval: 1.58, 3.55] cumulative trillions USD, with substantial societal losses. Subsidy needs are lowered to 0.93 [0.57, 1.22] cumulative trillions USD under stringent climate policies, with economic gains accruing not before mid-century. These findings highlight the critical role of climate policies in enabling a robust and societally desirable deployment strategy for CO₂ removal.

Keywords: Direct Air Capture, Uncertainty Quantification, Global Sensitivity Analysis, Mitigation

Introduction

In the last decade, the Paris Agreement and announcements of ambitious net-zero pledges by many countries increased the interest in deep mitigation pathways to limit global warming to well below 2°C. These pathways assume a transition to low-carbon energy sources combined with the use of carbon dioxide removal (CDR) technologies, essential for balancing emissions from 'hard-to-abate' sectors and absorbing excess CO₂ in the atmosphere [1]. However, CDR remains a subject of intense debate in the general public and the scientific community [2, 3]. This debate is centred around the deterrence these technologies may pose to mitigation [4, 5], inequality repercussions [6, 7], and removal costs [8, 9].

As of 2024, CDR methods are estimated to remove roughly 2 GtCO₂ per year, primarily (99.9%) in the land use, land-use change and forestry sector [10]. Accounting only for the 0.1%, novel CDR technologies such as direct air carbon capture and storage (DACCS) and bioenergy with carbon capture and storage (BECCS) are still in their infancy, and the scale of their future deployment is largely uncertain [10]. DACCS has several unique advantages compared to other CDR methods: it allows for permanent removal of CO₂, is less land-intensive, and enables straightforward accounting of removed emissions [11]. Relevant works highlight its potential in stringent mitigation scenarios [12–15]. However, as a new technology, significant uncertainties exist regarding the barriers to scaling DACCS at the levels needed to make a difference, and failing to account for them may significantly delay the ecological transition and generate stranded assets [16].

These uncertainties are both directly and indirectly related to the technology itself. Direct uncertainties concern the costs and performance of different DACCS technologies [8, 9, 17–19], their dependence on regional climatic conditions [20, 21], and the scale of market penetration (also called feasible deployment) [5, 17, 18, 22]. Indirect uncertainties stem mainly from the policy environment, shaped by emissions reduction ambitions, targeted support for DACCS, and interactions with other CDR options. This policy dependence is critical [23]: DACCS has few co-benefits compared with alternatives such as BECCS or afforestation, and the current need for CO₂ removal is limited. No countries currently include novel CDR methods in their nationally determined commitments [10], and for many sectors, reducing emissions remains cheaper than capturing and storing them with DACCS [11].

Different computational tools, such as integrated assessment models (IAMs), were developed or expanded to help policymakers navigate these uncertainties. Yet, most studies examined them in isolation rather than in an integrated fashion. Some analyzed only the uncertainty in feasible deployment, without accounting for other factors [4, 22]. Others explored socio-economic pathways and policy settings while keeping other inputs, such as costs or deployment limits, fixed [13, 15]. Where sensitivity analysis had been applied, it often relied on one-at-a-time changes in uncertain inputs [12, 24], covering only a small portion of the possible inputs space and overlooking interactions between variables [25]. A notable exception is a recent study that implemented multiple CDR technologies in a mixed-integer linear optimization model to design robust portfolios and assess the relative importance of different inputs using explainable machine learning indices [26]. Still, this work left – highly critical – policy

uncertainty unaddressed and represented technological uncertainty with only a few parameters. More generally, the existing literature shows a fragmentation due to the extreme complexity of the problem.

Building on previous works, we address this issue by implementing three DACCS technologies in the detailed-process integrated assessment model (IAM) WITCH [27]: liquid solvent, solid sorbent, and CaO ambient weathering. We characterize the uncertainties around DACCS deployment relying on probability distributions that reflect the most up-to-date understanding of the uncertain inputs, and implement two scenarios with increased climate ambitions. We then carry out the first global sensitivity analysis (GSA) of DACCS using advanced sensitivity analysis techniques based on Optimal Transport [28, 29]. The umbrella term GSA describes a set of tools to investigate how the variation in the output of a model can be attributed to variation of its inputs [30, 31]. In other words, GSA is a way to systematically address the role of numerical assumptions (the inputs) in supporting the decision-making process. In the context of climate mitigation research, GSA was used to explore robust abatement pathways [32], the importance of socio-economic assumptions [33], and technological characteristics [34], among others. GSA is a critical tool for understanding the behaviour of complex computational models, especially when those models inform high-stakes policy decisions [35]. Deploying novel Carbon Dioxide Removal (CDR) technologies such as DACCS falls within this category. On the one-hand side, these technologies are characterized by substantial uncertainties across technical, economic, and policy dimensions. On the other hand side, they hold the potential for notable societal gains or losses. Incorporating CDR into models without robust, multidimensional uncertainty analysis poses significant risks. Figure 1 summarizes the adopted workflow.

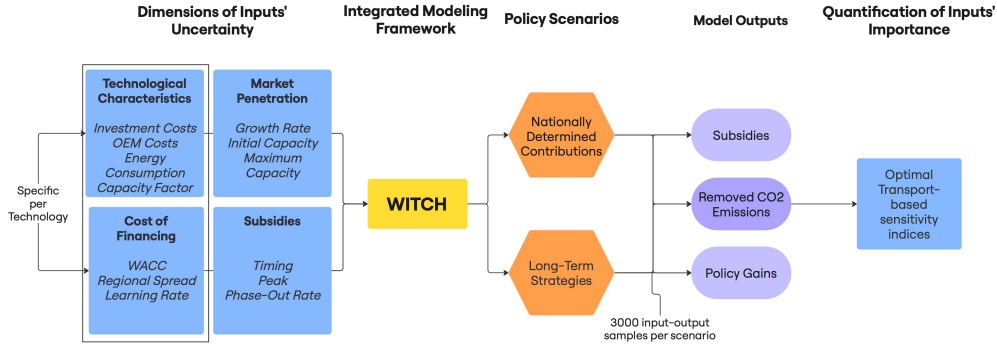


Fig. 1 The study explores four key dimensions of uncertainty: technological characteristics, market penetration, cost of financing, and subsidies using a probabilistic approach (see Supplementary Table 1). These uncertainties are integrated within the WITCH integrated assessment model. Superimposed on the probabilistic structure, two baseline scenarios are considered: Nationally Determined Contributions and Long-Term Strategies. The model produces three key outputs: net CO₂ removals, subsidies, and policy gains, which are then analysed using Optimal Transport-based sensitivity indices and other statistical methods.

Sensitivity Analysis for Technology Deployment

In our work, we use the newly developed Optimal Transport-based sensitivity indices [28, 29] (OT-based indices, henceforth) as a GSA tool. This method builds on the mathematical framework of Optimal Transport [36, 37], a field at the intersection of probability, statistics, and optimization. The OT-based indices offer several advantages that make them particularly well-suited to our application [38]. First, they are well-defined for multivariate outputs, like vectors and time-dependent curves. This property is practical when studying the deployment of new technologies, for which we are often interested in temporal dynamics. Second, unlike classical variance-based techniques, these indices remain easily interpretable when inputs are statistically dependent, allowing us to address realistic correlation structures among uncertain inputs. This property is essential in optimization models, where unfeasibilities may induce correlation structures in the inputs, even if they are independent in sampling. Third, their normalized $[0, 1]$ scale makes interpretation intuitive, and they can be estimated directly from Monte Carlo samples, avoiding the need for additional model runs or surrogate modelling.

Defining the input distributions is a crucial step in the GSA process. In this study, we examine 36 input variables grouped into four key dimensions of uncertainty (cf. Figure 1): technological characteristics, market growth, cost of financing, and subsidies. The technological characteristics are technology-specific and calibrated using a probabilistic DACCS cost model [8]. This category includes inputs such as capital expenditures, operational and maintenance costs, and energy requirements. To represent market growth, we constrain the expansion of DACCS deployment over time using a logistic growth function. This constraint ensures that investment decisions in each period are limited by the scale already achieved in previous periods. Market penetration input distributions are based on data from other technologies [22] and on reasonable assumptions. The cost of financing follows a recent implementation [39], with weighted average cost of capital values centred on estimates from the literature [40] and sampled from truncated Gaussian distributions to capture a broad range of plausible outcomes. Finally, subsidies are represented as a normative policy input, specified through a simple parametric function. Supplementary Table 1 summarises the input distributions, with further implementation details described in Section 6.

We complement this probabilistic analysis with a traditional scenario-based one to address the deep and unquantifiable uncertainty behind the international policy framework. We analyze the deployment of DACCS under two baseline scenarios to capture distinct policy trajectories and ambition levels:

- **Nationally Determined Contributions (NDC):** This scenario extrapolates the current short-term policy commitments from countries under the Paris Agreement. The NDC scenario assumes the continuation of existing climate policies without significant additional ambition, reflecting the current heterogeneous and moderate global policy landscape. This scenario is a benchmark of realistic yet unambitious international climate policy commitments.
- **Long-Term Strategies (LTS):** The LTS scenario represents an ambitious policy trajectory consistent with stringent global climate goals, where all major economies

146 implement enhanced policies aligned with net-zero targets by mid-century. It reflects
147 the net-zero commitments announced by several countries, involving extensive policy
148 support and substantial financial mechanisms to foster the deployment of advanced
149 mitigation technologies, including DACCS.

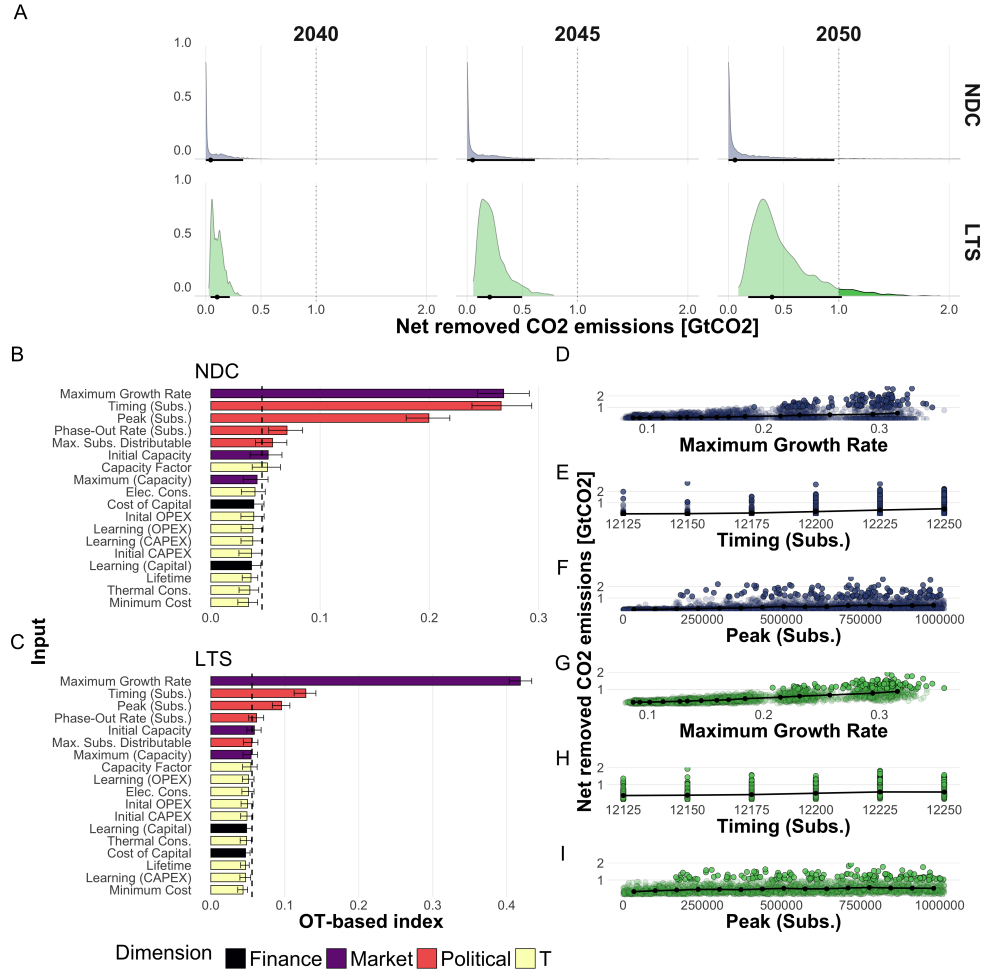


Fig. 2 A. Yearly net CO₂ emissions removed by DACCS between 2040 and 2050 in the two scenarios. Each plot represents the empirical probability density. Transparency identifies the threshold of 1 GtCO₂. The black bars below the plots represent medians and 5th-95th quantile ranges. B-C. Sensitivity analyses for net removed CO₂ emissions in the two scenarios. The x-axis represents the OT-based index. On y-axis, each bar represents the input. Error bars are the 95% bootstrapped confidence intervals. Colours represent the dimension of uncertainty. Inputs are ranked in descending order. Where inputs are differentiated by technology, we consider the maximum OT-based index among them. The dashed vertical line represents the irrelevance threshold. D-E-F. Partial dependency plots in the NDC scenario. The x-axis represents the input value, and the y-axis represents the corresponding net removed CO₂ emissions in 2050. The transparency is the 1 GtCO₂ threshold, and the black line represents the estimated conditioned mean. H-G-I. Partial dependency plots in the LTS scenario.

Determinants and bottlenecks of Gt-Scale Deployment

We start by analysing the patterns of deployment of DACCS over time, the scenarios, and their determinants. DACCS has the potential to grow under both baseline scenarios, but with distinct dynamics and only a small likelihood of reaching large-scale deployment by mid-century (Fig. 2, panel A). In the less ambitious NDC scenario, median CO₂ removals remain modest, rising from 0.04 GtCO₂ in 2040 to just 0.06 GtCO₂ by 2050. Notably, removals in 21% of the simulations remain below 1 MtCO₂, signalling near-zero deployment. Similarly, the probability of achieving gigaton-scale by mid-century is only 4%. Under the more stringent LTS policies, median removals grow more rapidly, reaching 0.10 GtCO₂ in 2040 and 0.39 GtCO₂ by 2050. Despite these differences, the probability of getting to gigaton-scale by 2050 remains low (6%). These findings suggest that the ambition of the climate targets is decisive in enabling DACCS to emerge as a meaningful mitigation option, regardless of other technological or economic uncertainties. At the same time, a long tail of high-removal outcomes exists in both scenarios, indicating that large-scale deployment remains a plausible, albeit unlikely, future.

Across both scenarios, we identify three key factors driving DACCS deployment in 2050 (Figure 2, panels B and C): the maximum deployment growth rate (*Maximum Growth Rate*), and the level and timing of peak subsidies (*Peak (Subs.)* and *Timing (Subs.)*, respectively). Among these, subsidies play a particularly pivotal role in shaping deployment trajectories under the less ambitious NDC scenario (Figure 2, panel B). In this context, they are needed to compensate for otherwise insufficient baseline policy incentives. Subsidies remain influential even under the more stringent LTS scenario (Figure 2, panel C), although their relative importance declines as climate targets become more ambitious. This decline indicates that while robust emissions reduction policies can lessen the need for subsidies, well-designed financial support may still be relevant to accelerate learning-by-doing and unlock gigaton-scale deployment.

In particular, the level of peak subsidies has a non-linear effect on the net removed CO₂ emissions, acting as a switch. No gigaton-scale deployment of DACCS occurs with subsidies below 425 USD/tCO₂ of peak value in both scenarios (Figures 2, panels F and I). Above this threshold, the net removed CO₂ emissions distribution reaches a plateau: further increasing the peak subsidy does not lead to a proportionally larger deployment nor significant changes in the marginal distribution. This visual intuition is confirmed by the local separations, which measure the importance of an input when fixed at a particular value (Supplementary Figure 1-2). We also performed the sensitivity analysis by filtering only peak subsidies below 1000 USD/tCO₂ to check the robustness of the findings, yielding similar results (Supplementary Figure 3).

Most technological characteristics, such as capital and operational costs or energy requirements, exert a limited and insignificant influence on DACCS deployment outcomes in both scenarios. This reflects the dominant role of subsidies and market penetration constraints in shaping deployment trajectories. While this finding may seem counterintuitive, it aligns with hypotheses in the existing literature [12, 22]. A partial exception is the capacity factor, which shows a possible influence under

the NDC scenario (Figure 2, panel B). Our results do not suggest that technological features are irrelevant, but rather that their impact is comparatively small. Taken together, these findings emphasize that the primary barriers to scaling DACCS lie not in refining technical specifications but in securing a supportive framework with stringent climate policies, targeted subsidies, and fast diffusion.

Economic Implications

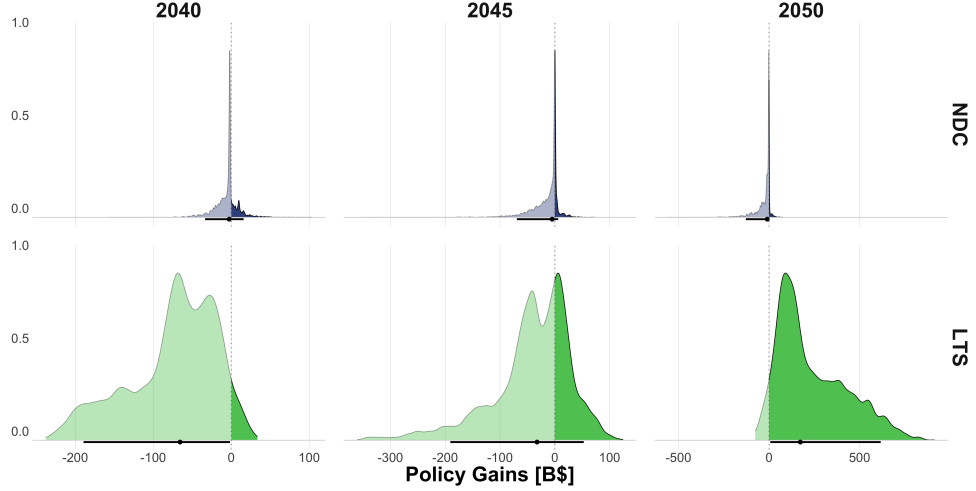


Fig. 3 Distribution of yearly policy gains as variation of GDP from baseline. Each plot represents the empirical probability density. Transparency identifies the zero threshold. The black bars below the plots represent medians and 5th-95th quantile ranges.

From an economic standpoint, deploying DACCS involves significant upfront costs and requires sustained support, particularly before any net benefits materialize. Under the NDC scenario, global GDP policy gains are characterized by a high density close to zero and a strongly skewed distribution, with long tails (Figure 3). Median GDP gains range from -3 billion USD in 2040 to -10 billion USD in 2050. In contrast, median gains increase significantly under the more ambitious LTS scenario, from -66 billion USD in 2040 to 173 billion USD by 2050. Losses are even greater than in the NDC scenario in the short- to mid-term, reflecting higher levels of DACCS deployment driven by more substantial climate commitments. Still, by the mid-century, median economic benefits would be considerable (173 billion USD). In both scenarios, the likelihood of positive outcomes is non-negligible and shows different trends. In the NDC scenario, it decreases from 21% in 2040 to 6% in 2050. In the LTS scenario, it grows from 5% in 2040 to 95% in 2050.

However, if we aim to analyze societal welfare, variation in consumption is a more relevant indicator. Using this metric, we find short- and mid-term losses in all feasible

runs (Supplementary Figure 4), which are compensated by long-term gains only in the LTS scenario. In some trajectories, net benefits exceed 4000 billion USD, highlighting the long-payback nature of DACCS (Supplementary Figure 5).

Overall, these results show that DACCS deployment may increase the burden of mitigation in the short- to mid-term. Moreover, the divergence between GDP- and consumption-based gains highlights a key feature of DACCS in the model: its deployment acts as a stimulus, boosting overall economic activity. However, these gains do not immediately translate into direct welfare benefits. The transition from stimulus for the economy to tangible welfare improvements appears only after mid-century.

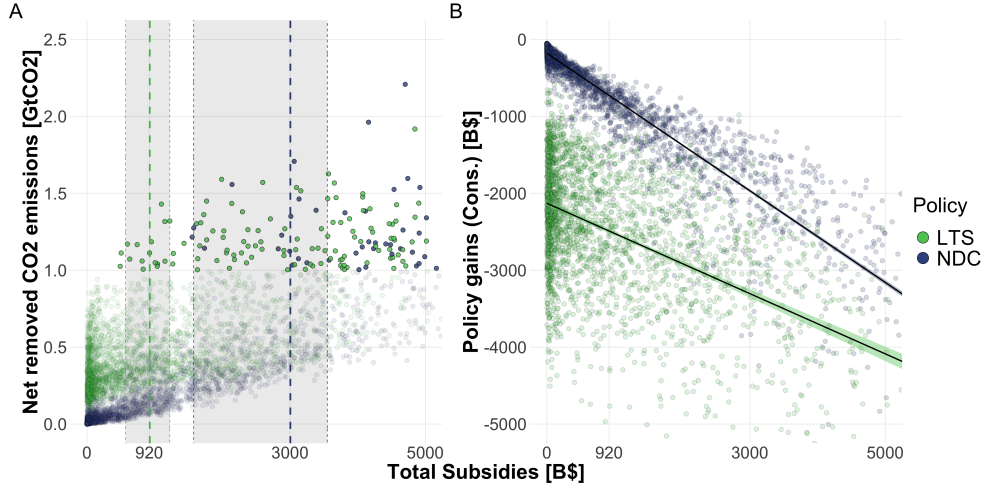


Fig. 4 A. Relationship between the net present value of the subsidies distributed between 2025 and 2050 and installed capacity in 2050. The colored vertical lines represent the 5th percentile of the distribution of the points above 1GtCO₂, and the shaded area is the 95% bootstrap confidence interval. Transparency identifies the threshold of 1 GtCO₂. B. Relationship between the net present value of the subsidies distributed between 2025 and 2050 and the net present value of the consumption-based policy gains between 2025 and 2050. The black line is the smoothing performed using a generalized additive model. Transparency identifies the zero threshold.

How much policy support is needed is key for understanding the viability and societal desirability of a DACCS programme at scale. We find a difference between scenarios in the level of support required to achieve gigaton-scale deployment (Figure 4, panel A). In the NDC scenario, scaling DACCS demands approximately 3000 billion USD in subsidies cumulatively over the next 25 years (95% CI: [1580, 3550] billion USD). In contrast, under the LTS scenario, the required subsidy volume is lower, but still large at around 930 billion USD (95% CI: [570, 1220] billion USD). The smaller amount reflects the presence of pre-existing carbon taxes and climate targets that curb the need for additional support, despite the higher volumes deployed.

This level of public support comes at societal costs. The relationship between the net present value of the subsidies and consumption losses is significantly negative

(Figure 3, panel B), indicating that increased support to DACCS generally reduces the net welfare benefit by mid-century. Notably, the regression intercept is significantly negative at −2130 billion USD, implying that, even in the absence of subsidies, the introduction of DACCS is associated with welfare losses by mid-century.

Discussion

In this work, we evaluate the role of direct air carbon capture and storage (DACCS) under different uncertainties, providing insights into the conditions required for DACCS to scale and the economic repercussions of its deployment. We draw on an up-to-date understanding of the uncertain inputs and advanced sensitivity analysis techniques.

The analysis reveals that gigaton-scale deployment is possible independently of the policy scenario, but different policy environments create distinct dynamics and challenges for scaling. Under weaker climate goals, diffusion barriers and subsidies are critical in enabling deployment. However, as mitigation ambition increases, market penetration barriers emerge as the dominant constraint, particularly the speed at which DACCS technologies can scale. On the economic side, our results indicate that positive economic returns are achievable around mid-century but only within ambitious climate mitigation frameworks. However, if we look at benefits in welfare, introducing DACCS as a mitigation option leads to losses until mid-century, independently of the ambition of the climate targets.

These results suggest that DACCS uptake in less ambitious policy environments may remain limited and economically unjustified. In a more stringent policy environment, DACCS deployment may increase the mitigation burden in the mid-term in favour of long-term gains. Thus, we suggest that relying on DACCS – at least on current technologies with limited maximal growth rates – is currently a dangerous bet. To deploy DACCS at scale, policymakers will have to address diffusion barriers, such as markets’ readiness to absorb and deploy carbon removal technologies, rather than focusing on decreasing the cost of the technology. While costs are more studied, these diffusion barriers are poorly understood, highly region-specific, and complex in their nature. As a complement/alternative, new DACCS technologies with different inherent technology characteristics and consequentially potentially lower diffusion barriers should be considered/supported [41].

From a methodological viewpoint, our study highlights several important issues. First, uncertainty quantification and global sensitivity analysis are essential to climate change research. Uncertainties should not be concealed but instead explained and discussed transparently; even in their presence, valuable insights can be derived about the research questions at hand. Second, recent advances in the GSA literature can provide helpful guidance for both modellers and decision-makers. Optimal Transport-based sensitivity indices are simple to interpret and to estimate, and rely on the well-studied theoretical framework of Optimal Transport. Finally, our results indicate that parametric uncertainty plays a significant role in shaping mitigation pathway projections. From a broader perspective, these points and the increased computational

power raise questions about whether and how parametric uncertainty should be incorporated into international climate science assessments such as the Intergovernmental Panel on Climate Change’s Assessment Reports.

Several limitations should be noted. The analysis does not account for political acceptability or social resistance to DACCS deployment, which may significantly influence feasibility. We do not explore structural model uncertainty, and future work should assess the robustness of these insights across alternative modelling frameworks. Moreover, the interplay between DACCS and other permanent CDR technologies, such as BECCS and enhanced weathering, has not been explored, and it is a valuable direction for future research.

Methods

WITCH Model

WITCH [27, 42, 43] is a detailed-process Integrated Assessment Model that combines the economy, climate, and energy systems in a unified framework. In WITCH, the world is partitioned into 17 regions, denoted with $\mathcal{N}$. An intertemporal optimal growth model represents the economy of each region. The representation of the energy sector is hard-linked with the rest of the economy so that energy investments are chosen optimally, together with the other macroeconomic variables. The temporal horizon spans from 2020 to 2150, with 5-year timesteps.

WITCH has two relevant features to analyse emerging technologies: endogenous learning and accounting for the cost of capital. Each technology is represented by technological characteristics that can change following learning-by-doing and/or learning-by-researching frameworks. This feature is desirable when modelling novel technologies like DACCS. Moreover, WITCH has been recently expanded to account for the cost of capital [39]. This feature enables the representation of how access to affordable finances varies across technologies, time, and regions.

Model Equations

We integrate a portfolio of three direct air carbon capture and storage (DACCS) technologies into the WITCH model: liquid solvent (LS), solid sorbent (SS), and calcium oxide ambient weathering (CaO). These technologies are indexed by $d \in \{LS, SS, CaO\}$. In terms of energy inputs, SS and CaO are assumed to be fully electrified, while LS requires both electricity and natural gas.

Investments in DACCS technology d , at time t in region n , are denoted as $I(d, t, n)$. Installed capacity $K(d, t, n)$ evolves according to:

$$K(d, t + 1, n) = (1 - \delta_d)K(d, t, n) + \frac{I(d, t, n)}{C_{\text{cap}}(d, t, n)\omega_{\text{adj}}(d, t, n)}, \quad (1)$$

where δ_d is the depreciation rate derived from the lifetime LT_d , $C_{\text{cap}}(d, t, n)$ denotes the capital expenditure per unit of capacity, and $\omega_{\text{adj}}(d, t, n)$ is the weighted adjusted cost of capital. The parameter $\omega_{\text{adj}}(d, t, n)$ is calculated by removing the endogenous

314 interest rates ($IR(t, n)$) from the weighted average cost of capital (WACC) denoted
 315 by $\omega(d, t, n)$ [39]:

$$\omega_{\text{adj}}(d, t, n) = \frac{\sum_{\tau=0}^{LT_d} (1 + IR(t + \tau, n))^{-\tau}}{\sum_{\tau=0}^{LT_d} (1 + \omega(d, t + \tau, n))^{-\tau}}. \quad (2)$$

316 To capture market penetration constraints, we impose a logistic growth bound on
 317 capacity expansion [22]:

$$\Delta K(d, t + 1, n) \leq kK(d, t, n) \left(1 - \frac{K(d, t, n)}{L_n} \right) + K_0, \quad (3)$$

318 with $\Delta K(d, t + 1, n) = K(d, t + 1, n) - K(d, t, n)$, k as the maximum growth rate, L_n
 319 the regional saturation level, and K_0 a constant enabling initial deployment in regions
 320 with no prior capacity.

321 Operational expenditures are captured as:

$$C(t, n) = \sum_d C_{\text{op}}(d, t, n)K(d, t, n) + C_{\text{stor}}(t, n), \quad (4)$$

322 where $C_{\text{op}}(d, t, n)$ includes costs related to labor, maintenance, and consumables, and
 323 $C_{\text{stor}}(t, n)$ is the endogenous cost of storage.

324 Capital and operating costs, and the weighted adjusted cost of capital decline over
 325 time through endogenous learning, represented by:

$$C_{\text{cap}}(d, t, n) = C_{\text{cap0}}(d, n) \left(\frac{1}{C_{\text{np}}} \sum_{\tau=1}^{t-1} \frac{I(d, \tau, n)}{C_{\text{cap}}(d, \tau, n)} \right)^{b_{\text{cap}, d}}, \quad (5)$$

326 where $C_{\text{cap0}}(d, n)$ is the initial capital cost, C_{np} is the nameplate capacity used to
 327 calibrate the learning parameters, and $b_{\text{cap}, d}$ is the technology-specific experience rate
 328 exponent. The same equation applies to C_{op} and ω as well with specific initial values
 329 (C_{op0} and ω_0) and learning parameters ($b_{\text{op}, d}$ and b_{fin}).

330 Subsidies are implemented in the model as carbon taxes on top of the baseline
 331 scenario assumptions. Their functional form is:

$$s(t) = \begin{cases} S \frac{t-2025}{T-2025}, & \text{if } t \leq T \\ S e^{-\alpha(t-T)} & \text{otherwise} \end{cases}. \quad (6)$$

332 The function is parametrized by the peak S , the timing of the peak T , and the phase-
 333 out rate α . We also constraint the maximum subsidies distributable to be at most a
 334 fraction y_{frac} of the regional GDP.

Input Calibration

The selection of the input distribution is a delicate task extensively discussed in the risk-assessment literature [38, 44, 45]. We follow a standard approach: we use up-to-date distributions found in the literature when possible. Otherwise, we assign a plausible distribution, trying to explore the input space. Supplementary Table 1 contains a summary of the input distributions.

The technological characteristics are calibrated using a probabilistic DACCS cost model [8]. This input dimension includes: the initial capital and operational and maintenance expenditures ($C_{\text{cap}0}$ and $C_{\text{op}0}$), corresponding learning rates ($b_{\text{cap},d}$ and $b_{\text{op},d}$), capacity factors (f_d), energy requirements (ζ and η), and lifetimes (LT_d).

Financing costs lack probabilistic characterizations in the literature, and no data exist on the weighted average cost of capital (WACC) for DACCS. We therefore assign to the WACC for Europe a truncated Gaussian distribution centred on values reported in related studies [8, 40], allowing for a broad range of possible WACCs. For the other 16 regions, we sample from other technologies' WACC data and apply the same relative regional differences. Finally, we assume a uniform distribution centred on the default value for the learning-by-financing input b_{fin} .

The market penetration constraint follows the logistic growth constraint (Equation (3)). For the maximum market growth rate (k), we base the distribution on technological analogue data [22], filter out values below 0.09 to reduce infeasibilities, and generate a continuous distribution using a kernel density estimator [46]. We assume a uniform distribution for the initial capacity K_0 , reflecting the absence of prior knowledge and aligning with GSA practice in IAMs [47]. The regional saturation level L_n is derived in three steps. First, we identify areas with a mean annual temperature above -15°C [20] using historical data [48]. Second, we estimate available land by country suitable for DACCS siting using FAO land-use data [49, 50]. Third, we combine these with DACCS land-use factors [51] to determine maximum installable capacity per region. These values serve as regional capacity shares, while the global saturation level is drawn from a uniform distribution centred on the maximum value in the AR6 database [22]. While simplified, this approach offers a first-order estimate of a critical constraint in DACCS deployment modelling. Supplementary Table 2 displays the range of the global and regional saturation levels.

Subsidies are modelled as a simple parametric function governed by four intuitive variables: timing (T), peak value (S), phase-out rate (α), and maximum subsidies distributable (y_{frac}). Since these inputs are normative, we design distributions to explore the space thoroughly rather than be policy-realistic. We assume a uniform distribution for the T , S , and y_{frac} , while we assign to α a gamma distribution to address the possibility of fast decays in policy support. We assume that only regions with reasonably ambitious LTS policies subsidize DACCS, defined as an emissions reduction of at least 50% by the end of the century. By using this threshold, we filter out five of the seventeen regions: **laca** (Latin America and Caribbean), **mena** (Middle East and North Africa), **mexico** (Mexico), **sasia** (South Asia, excluding India), **ssa** (Sub-Saharan Africa), **te** (Non-EU Eastern European countries).

Quantities of Interest

We consider three quantities of interest: the yearly net removed CO₂ emissions, the policy gains, and the total subsidies. The yearly net removed CO₂ emissions are defined as:

$$E(t) = \sum_{n \in \mathcal{N}} \sum_d f_d K(d, t, n) \quad \text{for } t \in \{2040, 2045, 2050\}, \quad (7)$$

where K is the installed capacity (Equation (1)), and f_d is the capacity factor. In the uncertainty quantification, we separately analyse the three quantities of interest. In the GSA step, we consider the multivariate output $(E(2040), E(2045), E(2050))$.

The yearly policy gains for a scenario $s \in \{NDC, LTS\}$ are defined as:

$$G(t) = \sum_{n \in \mathcal{N}} [Q(t, n) - Q_s(t, n)] \quad \text{for } t \in \{2025, 2030, \dots, 2050\}, \quad (8)$$

where Q is either the consumption or the GDP in the specific Monte Carlo run, and Q_s is the consumption or GDP in a run for scenario s with small DACCS deployment. When aggregating in time, we consider the net present value as:

$$G = \sum_{t=2025}^{2050} G(t) \left(\sum_{\tau=t}^{t+4} \frac{1}{(1+\rho)^{\tau-2025}} \right), \quad (9)$$

We assume a discount rate of 3% per year and account for the 5-year timesteps through the sum indexed by τ .

The total subsidies are the actual subsidies handed out, in the form:

$$TS = \sum_{t=2025}^{2050} \sum_{n \in \mathcal{N}} \sum_d f_d K(d, t, n) s(t) \left(\sum_{\tau=t}^{t+4} \frac{1}{(1+\rho)^{\tau-2025}} \right). \quad (10)$$

Optimal Transport-based Sensitivity Indices

Here, we present a succinct overview of the subject. We refer to more detailed works for an extended discussion on Optimal Transport [36, 37], the Optimal Transport-based sensitivity indices [28, 29], and the computational aspects of indices estimation [37, 52].

Let us consider two probability distributions, $\mathbb{P}$ and $\mathbb{P}'$, defined over the same space $\mathcal{Y} \subseteq \mathbb{R}^m$. Let us also define a ground cost $k: \mathcal{Y} \times \mathcal{Y} \rightarrow [0, +\infty]$ over the space $\mathcal{Y}$. The optimal transport (OT) problem can be expressed as the problem of finding the least-cost coupling between $\mathbb{P}$ and $\mathbb{P}'$ given the ground cost function. The couplings, also called transport plans, are joint probability measures on $\mathcal{Y} \times \mathcal{Y}$, such that their marginals are $\mathbb{P}$ and $\mathbb{P}'$.

When the ground cost is the squared Euclidean distance, the OT problem defines a distance over the space of probability measures, called the Wasserstein distance, that

405 can be expressed as:

$$\begin{aligned}
K(\mathbb{P}, \mathbb{P}') &= \text{WB}(\mathbb{P}, \mathbb{P}') + \Gamma(\mathbb{P}, \mathbb{P}') \\
&= \|m - m'\|_2^2 + \text{Tr}\left(\Sigma + \Sigma' - 2\left(\Sigma'^{\frac{1}{2}}\Sigma\Sigma'^{\frac{1}{2}}\right)^{\frac{1}{2}}\right) + \Gamma(\mathbb{P}, \mathbb{P}'), \tag{11}
\end{aligned}$$

406 where m , m' and Σ , Σ' are the means and covariance matrices of $\mathbb{P}$ and $\mathbb{P}'$ respec-
407 tively, and Tr is the trace operator, summing all diagonal entries of a square matrix.
408 We call $K(\mathbb{P}, \mathbb{P}')$ the OT cost. The sum of the first two terms on the second line of
409 Equation (11) defines the Wasserstein–Bures semi-metric, denoted by $\text{WB}(\cdot, \cdot)$. The
410 first term captures the cost of aligning the mean values of the distributions $\mathbb{P}$ and $\mathbb{P}'$,
411 corresponding to their first-order moments. The second term represents the optimal
412 cost of matching their variance-covariance matrices, i.e., the second-order moments.
413 The third term, $\Gamma(\cdot, \cdot)$, accounts for the differences in higher-order moments. We refer
414 to it as the residual term, which generally lacks a closed-form expression. As a result,
415 the full Wasserstein distance between two arbitrary distributions cannot be derived
416 analytically.

417 Let us consider a model f with inputs $\mathbf{X} = (X_1, \dots, X_n)$ and (possibly multivari-
418 ate) output $\mathbf{Y} \in \mathcal{Y}$. Let us further define the unconditioned output distribution as $\mathbb{P}_{\mathbf{Y}}$,
419 and the distribution of the output fixed one input X_i as $\mathbb{P}_{\mathbf{Y}|X_i}$. The OT cost $K(\mathbb{P}, \mathbb{P}')$
420 can be used to define a measure of statistical association between the output $\mathbf{Y}$ and
421 the input X_i as:

$$\xi^K(\mathbf{Y}, X_i) = \mathbb{E}_{X_i}[K(\mathbb{P}_{\mathbf{Y}}, \mathbb{P}_{\mathbf{Y}|X_i})]. \tag{12}$$

422 In this case, we call the function $\gamma(X_i) = K(\mathbb{P}_{\mathbf{Y}}, \mathbb{P}_{\mathbf{Y}|X_i})$ local separation measure. We
423 can derive an upper bound for $\xi^K(\mathbf{Y}, X_i)$:

$$\xi^K(\mathbf{Y}, X_i) \leq 2\mathbb{V}[\mathbf{Y}], \tag{13}$$

424 where $\mathbb{V}[\mathbf{Y}]$ is the sum of the diagonal elements of the variance-covariance matrix of
425 the output(s) $\mathbf{Y}$. Since $\mathbb{V}[\mathbf{Y}] > 0$, we can further define the Optimal Transport-based
426 sensitivity index (OT-based index) as:

$$\iota^K(\mathbf{Y}, X_i) = \frac{\xi^K(\mathbf{Y}, X_i)}{2\mathbb{V}[\mathbf{Y}]}. \tag{14}$$

427 This index has several desirable properties described in [53]. First, $\iota^K(\mathbf{Y}, X_i) \geq 0$,
428 and $\iota^K(\mathbf{Y}, X_i) = 0$ if and only if $\mathbf{Y}$ and X_i are independent. This is called the zero-
429 independence property. Second, $\iota^K(\mathbf{Y}, X_i) \leq 1$ and $\iota^K(\mathbf{Y}, X_i) = 1$ if and only if there
430 exists a measurable function $\mathbf{g}$ such that $\mathbf{Y} = \mathbf{g}(X_i)$. This second property is called
431 max-functionality. Together, these two properties enable the indices to give synthetic
432 but comprehensive information on the statistical association between two random
433 variables. Moreover, the decomposition in Equation (11) enables the decomposition
434 of the OT-based indices as $\iota^K(\mathbf{Y}, X_i) = \iota^V(\mathbf{Y}, X_i) + \iota^\Sigma(\mathbf{Y}, X_i) + \iota^\Gamma(\mathbf{Y}, X_i)$. Here,
435 $\iota^V(\mathbf{Y}, X_i)$ estimates the importance of X_i on the mean of $\mathbf{Y}$, $\iota^\Sigma(\mathbf{Y}, X_i)$ quantifies the

importance of X_i on the variance-covariance matrix of $\mathbf{Y}$, and $\iota^\Gamma(\mathbf{Y}, X_i)$ identifies the higher order effects.

Even though the indices possess the zero-independence property, the numerical estimation may induce some non-zero index values even in the case of independence. The answer to the question of whether these inputs are influential depends on understanding whether the non-null estimates result from numerical noise. We address this problem by introducing an auxiliary random variable X_{dummy} , independent of the output $\mathbf{Y}$ by construction, and computing its OT-based index $\iota^K(\mathbf{Y}, X_{dummy})$. Given the zero-independence property, a non-zero estimate of $\iota^K(\mathbf{Y}, X_{dummy})$ is due to numerical noise. Thus, we can use this value as an irrelevance threshold.

Design of experiment

We generate 3,000 input vectors drawing from a joint distribution constructed from the marginal distributions shown in Supplementary Table 1. The data-driven inputs are sampled using the probabilistic model accompanying the related work [8]. The *Maximum Growth Rate* (k) is sampled using a kernel density estimator implemented in the `ks` R package [54]. The remaining parameters are sampled using Latin Hypercube Sampling (LHS). Specifically, we generate 30 LHS designs with 100 points each using the `randtoolbox` R package [55], transforming the uniformly distributed samples into the target distributions via the inverse transform method.

To leverage high-performance computing capabilities, the full experimental design is partitioned into 100 equally sized clusters to enable parallel execution. Before clustering, all inputs are transformed into quantile space to ensure uniform scaling. Cluster centroids are generated using a Sobol' sequence [56] to ensure good space-filling properties. The clustering is formulated as a balanced optimal transport problem, assigning each design point to its nearest centroid while preserving uniform cluster sizes. The optimal transport problem is solved using the simplex method implemented by the `transport` R package [57]. Let $\{x_i\}_{i=1}^{3000}, \{c_j\}_{j=1}^{100} \subset [0, 1]^{36}$ be two sets of points. Defined the cost of assigning a point x_i to a centroid c_j as $k_{ij} = \|x_i - c_j\|^2$, the mathematical formulation of the problem is:

$$\begin{aligned}
& \min_{\pi_{ij}} && \sum_{i=1}^{3000} \sum_{j=1}^{100} k_{ij} \pi_{ij} \\
& \text{s.t.} && \sum_{j=1}^{100} \pi_{ij} = 1 \quad \forall i = 1, \dots, 3000 \\
& && \sum_{i=1}^{3000} \pi_{ij} = 1 \quad \forall j = 1, \dots, 100 \\
& && 0 \leq \pi_{ij} \leq 1 \quad \forall i, j
\end{aligned} \tag{15}$$

Given the non-linear nature of the WITCH model, convergence speed is improved by supplying informed initial values. For each scenario, we first run the model using the mean values of all inputs. Then, for each cluster, a greedy nearest-neighbour algorithm

orders the 30 points starting from the mean point, minimizing the Euclidean square distance in quantile space. This ordering promotes faster convergence during model execution. The result is a set of 100 parallelizable and internally ordered clusters, each composed of 30 design points. The model is solved using the CONOPT3 solver on 3rd-generation Intel Xeon Scalable processors. Then, we compute the sensitivity indices using the `gsaot` R package [52]. The whole pipeline is implemented using the `targets` R package [58], enabling reproducibility and interpretability.

Supplementary information.

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Declarations

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Optimal climate policy under tipping risk and temporal risk aversion

Romain Fillon^{1,a,b}, Céline Guivarch^b, Nicolas Taconet^{b,c,d}

^a*Université Paris-Saclay, INRAE, AgroParisTech, Paris-Saclay Applied Economics, F-91120, Palaiseau, France*

^b*CIREN, AgroParisTech, CIRAD, CNRS, EHESS, Ecole des Ponts ParisTech, Univ Paris-Saclay, UMR 8568. CIREN, 94736 Nogent-sur-Marne, France*

^c*Potsdam Institute for Climate Impact research - Member of the Leibniz Association, Potsdam, Germany*

^d*Technical University Berlin, Germany*

Abstract

We investigate the implications of absolute risk aversion with respect to intertemporal utility, i.e. *temporal* risk aversion, in the presence of a stylized climate tipping risk affecting productivity irreversibly. Optimal climate policy is more stringent under temporal risk aversion, in order to reduce all present and future probabilities of crossing the tipping point and avoid a situation where all generations are badly off. Temporal risk aversion implies a 30% increase in the social cost of carbon (SCC) under our benchmark calibration and for a 10% irreversible increase in the level of economic damage from climate change. The optimal SCC under temporal risk aversion increases sharply with the level of damage brought by a potential tipping point.

Keywords : stochastic climate-economy modelling, risk-sensitive recursive preferences, environmental policy, risk aversion. **JEL classification** : D61, D63, D71, D81, Q54, Q58.

¹Corresponding author: rfillon@protonmail.com

1. Introduction

When it comes to decision-making, risk is all around. But the concept is equivocal. First, it can refer to a univariate risk bearing on a single prospect. The seminal work from Pratt [42] and Arrow [6] introduced this risk into the analysis of decision-making through univariate measures of absolute and relative risk aversion within expected utility theory. A substantial body of literature has developed to generalise these measures of risk aversion to multivariate risks [31]. A risk-averse portfolio manager does not sum the risk of each asset, but considers the aggregate risk bearing on the portfolio. Indeed, a positive correlation between these asset risks increases the aggregate risk. In intertemporal settings, the absolute risk aversion with respect to aggregate intertemporal risk is called the *temporal risk aversion* [14]. The standard discounted expected utility model assumes temporal risk-neutrality [2]. This assumption has large implications as it implies that the decision-maker has no preference on the correlation between individual risks. Introducing absolute risk aversion with respect to intertemporal utility, i.e. temporal risk aversion, on the other hand, allows to consider risk bearing on aggregate intertemporal utility. It can explain agent's intertemporal decisions [11, 15]. It is also of interest from a normative point of view, to define optimal policies in risky social situations that involve several successive generations whose welfare is correlated.

A prominent example of intertemporal social risk management is climate policy-making. A major concern of climate policy-making is the possibility of non-linearities such as tipping points in the climate system. Once some thresholds for greenhouse gas concentrations in the atmosphere are exceeded, the state of the climate system could be radically and irreversibly altered. Tipping elements with significant economic implications have been identified, including the slowdown of the Atlantic Meridional Overturning Circulation, the West Antarc-

28 tic ice sheet disintegration, the Amazon rainforest dieback, or the Greenland ice
 29 sheet disintegration [5]. In the states of the world where the tipping point oc-
 30 curs, the welfare of all subsequent generations is affected by this qualitative
 31 regime change. Consequently, considering absolute risk aversion with respect
 32 to intertemporal utility becomes imperative due to the substantial impact on
 33 intertemporal welfare.

34 Temporal risk aversion can be interpreted as positive intertemporal correla-
 35 tion aversion [44], as positive intertemporal correlation implies a larger aggregate
 36 risk over intertemporal utility. A temporally risk-averse social planner prefers
 37 the welfare of different generations to be negatively or not correlated rather
 38 than positively correlated, in order to lower the risk on the aggregate outcome.
 39 In other words, the temporally risk averse social planner would be ready to give
 40 up some social welfare to prevent a situation where the tipping point is crossed
 41 and all subsequent generations are badly off. Thus, this social diversification
 42 strategy is appealing from a normative point of view when facing irreversible
 43 catastrophic tipping risks. Also, from a positive point of view, empirical elic-
 44 itations of individual preferences suggest that individual agents might exhibit
 45 positive correlation aversion [24, 3, 27, 45, 34].

46
 47 In this article, we investigate how temporal risk aversion may affect optimal
 48 climate policy. We analyze both analytically and numerically why, how and by
 49 how much two social planners, i.e. a temporally risk-neutral and a temporally
 50 risk-averse planner, differ in their optimal policy under risk. We focus on a
 51 specific type of risk: a climate tipping risk. We use a dynamic stochastic climate-
 52 economy model [28, 48] and extend it to an alternative social welfare function
 53 which allows the analysis of temporal risk aversion: the risk-sensitive preferences
 54 axiomatized in Hansen and Sargent [29]. By comparing optimal climate policies

55 under risk-sensitive preferences with those under the standard additive form
 56 of expected discounted utility, which assumes temporal risk-neutrality, we shed
 57 light on the implications of temporal risk aversion for policy design.

58 We find that, in the presence of a tipping risk, climate policy is more strin-
 59 gent under risk-sensitive preferences. The social planner under risk-sensitive
 60 preferences is willing to sacrifice more today to reduce all present and future
 61 probabilities of crossing the tipping point to avoid a situation of low overall
 62 intertemporal utility level. The difference in optimal climate policy between the
 63 two planners increases more than proportionally to the increase in the possible
 64 shock or in the temporal risk aversion. Under our benchmark calibration, a
 65 change from additive to risk-sensitive preferences implies a 30% increase in the
 66 social cost of carbon (SCC) for a 10% irreversible increase in the damage fac-
 67 tor. Switching from additive to risk-sensitive preferences under a 10% possible
 68 shock is equivalent to a 5 percentage points increase in the shock if we keep
 69 additive preferences. The difference between the two social choice criteria in-
 70 creases steeply with risk. Furthermore, other things being equal, a 50% decrease
 71 in pure time preference (from 1.5% to 1% yearly) is needed to obtain the same
 72 optimal policy under additive preferences as under risk-sensitive preferences for
 73 a 10% tipping risk and under our benchmark calibration. Thus, a change in the
 74 structure of the social welfare function can be directly compared to a change in
 75 the value of some parameters that have been highly debated. Finally, we use
 76 an analytical decomposition of our optimal policy program to derive the key
 77 channels through which a tipping risk affects optimal policy under both social
 78 welfare functions.

79
 80 Our work contributes to the literature aiming to enhance the integration of
 81 different types of risk, particularly the risk of climate tipping points [36, 52]

82 [19], into stochastic integrated assessment models (IAM). The first integrated
 83 climate-economy models were deterministic, e.g. Nordhaus [40]. These mod-
 84 els did not allow for a proper consideration of risk and uncertainty in planner's
 85 decisions, even when Monte Carlo analyses were conducted [21]. In parallel, con-
 86 tributions to modeling endogenous catastrophic environmental risk were mostly
 87 stylized [20, 50, 14]. In particular, these models are based on the assumption
 88 that welfare after the catastrophic event is exogenous and independent of the
 89 planner's actions. Tipping points are less extreme than catastrophes after which
 90 production and consumption would be exogenous and independent of the plan-
 91 ner's decisions. Indeed, these are ecological regime shifts with large economic
 92 consequences rather than complete economic or institutional collapses. These
 93 events are also different from reversible extreme events that occur as one-off
 94 catastrophes along a smoothly evolving climate regime with fluctuations, tra-
 95 ditionally modelled with Poisson and Wiener processes in the macroeconomics
 96 literature on disasters, e.g. in Bretschger and Vinogradova [17]. Departing from
 97 the assumption of a geometric Brownian motion with rare and reversible catas-
 98 trophic events, we study irreversible regime changes. This modelling approach
 99 has counterparts in the real business cycles literature studying markov switching
 100 rational expectations models with Bayesian learning, e.g. in Bullard and Singh
 101 [18].

102 Our contribution confronts the standard discounted expected utility model
 103 with an alternative criterion: a risk-sensitive criterion stemming from social choice
 104 theory and axiomatized in Bommier et al. [13]. Exploration of alternative social
 105 choice criteria under endogenous climate change was undertaken to introduce
 106 relative risk aversion under Epstein-Zin-Weil preferences [8, 51], a robust control
 107 penalty [46] and ambiguity aversion under isoelastic preferences in a setting with
 108 uncertainty [37]. In comparison with EZW preferences, risk-sensitive preferences

are the only recursive preferences axiomatized by Kreps and Porteus [33] that admit a separation of risk and intertemporal attitudes, while being monotone [13]. This desirable normative property ensures that a more risk-averse planner consistently prioritizes risk reduction. Those preferences can be defined through the following recursion [29, 13]:

$$V_t = \begin{cases} (1 - \beta) u_t + \beta \mathbb{E}[V_{t+1}] & \text{if } \epsilon = 0 \\ u_t - \frac{\beta}{\epsilon} \ln[\mathbb{E}(\exp[-\epsilon V_{t+1}])] & \text{if } \epsilon \neq 0 \end{cases} \quad (1)$$

with u_t the instantaneous utility at time t , β a discount factor derived from pure time preference and ϵ the temporal risk aversion. We hereafter use the denomination of risk-sensitive preferences only for those stationary preferences for which the social planner is at least as risk averse ($\epsilon > 0$) as a standard planner with additive preferences. Cases where the social planner is temporally risk-seeking ($\epsilon < 0$) are not discussed because of potential nonconvexity issues [15]. A temporally risk-seeking planner would choose a max-max strategy and positive correlation between the social gambles. If $\epsilon = 0$, then the social planner is temporally risk-neutral, which comes down to the additive form.

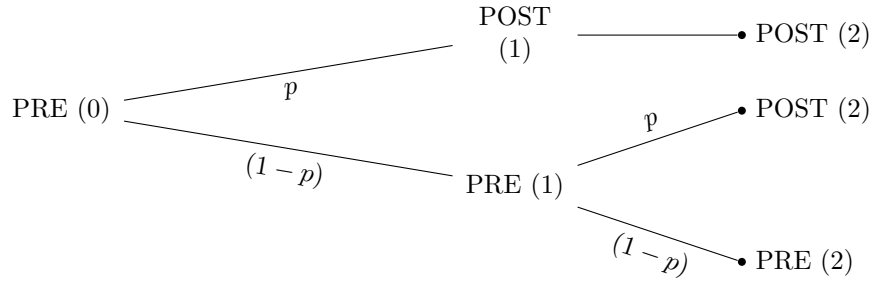
Firstly, we present our modelling approach (section 2): a dynamic stochastic climate-economy integrated model with a stylized tipping risk, in which we compare two alternative social welfare functions. Then, we discuss analytically how temporal risk aversion affects optimal policy under a tipping risk (section 3). Finally, we quantify numerically the differences between the two social welfare functions under a tipping risk (section 4).

2. A dynamic climate-economy stochastic model

2.1. A simple illustration

Firstly, we illustrate the significance of temporal risk aversion in the analysis of climate tipping risks using a simplified scenario. Consider three consecutive

time periods, representing distinct generations. Two climate regimes exist: pre-tipping (PRE) and post-tipping (POST), each associated with different levels of economic damage. Each generation t can either be in a high (PRE) or a low (POST) welfare regime, described by the variable u_i^t , $i \in (pre, post)$, $t \in 1, 2$. We assume that instantaneous welfare function in each potential situation is the same for both generations, i.e. $u_i^1 = u_i^2$.



We assume away time discounting and assume that the social planner has no preference on the order of the attributes and no preference for early resolution of uncertainty. Under the conditions listed above, a temporally risk-neutral social planner would be indifferent between the two following lotteries [10]:

$$\left\{ \begin{array}{l} (u_1^{post}, u_2^{post}) \text{ with probability } 1/3 \\ (u_1^{pre}, u_2^{post}) \text{ with probability } 1/3 \\ (u_1^{pre}, u_2^{pre}) \text{ with probability } 1/3 \end{array} \right. \sim \left\{ \begin{array}{l} (u_1^{post}, u_2^{post}) \text{ with probability } 1/2 \\ (u_1^{pre}, u_2^{pre}) \text{ with probability } 1/2 \end{array} \right. \quad (2)$$

A social planner under additive preferences would be indifferent between the two social lotteries A and B as the additive form assumes temporal risk-neutrality, while a temporally risk-averse social planner has a preference for lottery A. In other words, a temporally risk-averse social planner is willing to pay a temporal risk premium to hedge risks across generations and reduce the probability of complete failure across all generations.

In addition to positive intertemporal correlation aversion, temporal risk aver-

155 sion bears preference for catastrophe avoidance² [14], i.e. preference for a mean-
 156 preserving contraction in the distribution of catastrophic risks. The preference
 157 for catastrophe avoidance is highly debated in the literature for two main rea-
 158 sons. First, it is not clear that individual agents are catastrophe-averse [43].
 159 Furthermore, preference for catastrophe avoidance may be seen as unethical as
 160 a catastrophe-averse planner prefers to concentrate risk on a single generation
 161 rather than spreading it evenly [25]. Consequently, Fleurbaey [26] highlights
 162 that catastrophe aversion might be appealing only if the catastrophe has a mul-
 163 tiplier effect through externalities in society. The possible nonconvexities in
 164 the human-environment system, enhanced by ecological thresholds like climate
 165 tipping points, do have this multiplier property. Indeed, in the states of the
 166 world where the tipping point occurs, the regime change is *irreversible* and has
 167 an impact on all future generations.

168

169 We have described in a simple illustration the importance of temporal risk
 170 aversion in risky intertemporal settings. We now present a full-fledged stochastic
 171 climate-economy model to analyse and quantify the importance of temporal risk
 172 aversion for the definition of optimal climate policy under a tipping risk.

173 2.2. The model

174 A climate-economy integrated assessment model aims to study the inter-
 175 actions between the economy and the climate system. We introduce a simple
 176 growth model *à la Ramsey*, add a stylized representation of the climate dynam-
 177 ics and an endogenous stochastic tipping point in the climate system. We build
 178 on Guivarch and Pottier [28] and Taconet et al. [48], update the economic dy-
 179 namics to match DICE-2016 [39] and use an alternative social welfare function.

²If the social planner is temporally risk-seeking ($\epsilon < 0$), she favors risk equity, i.e. equalizing and spreading the risk among generations.

180

181 **Economy** In our global model, a single good is produced at each period
 182 t using two production factors, endogenous capital K_t and exogenous labour
 183 L_t , through a Cobb-Douglas production function $F(K_t, L_t) = A_t K_t^\alpha L_t^{1-\alpha}$ with
 184 exogenous Hicks-neutral technological change. The gross output $F(K_t, L_t)$ is
 185 affected by a damage factor $\Omega_t(T_t)$ that increases with global average tem-
 186 perature T_t . Net output Y_t is derived from the gross output net of damage:
 187 $Y_t = \Omega_t(T_t)F(K_t, L_t)$. Capital dynamics is determined by δ , the per-period cap-
 188 ital depreciation, and s_t , the savings rate. It writes: $K_{t+1} - K_t = -\delta K_t + s_t Y_t$.
 189 Gross output induces emissions, which can be mitigated at a certain cost. The
 190 social planner trades off consumption C_t , mitigation costs (which represent a
 191 share Λ_t of Y_t), and investment: $C_t = Y_t(1 - \Lambda_t - s_t)$. The mitigation cost Λ_t
 192 depends on the abatement rate μ_t and on the cost of the abatement technology
 193 that decreases due to exogenous technical progress. The cost of the abatement
 194 technology is calibrated on Nordhaus [39] as other parameters of the economic
 195 module.

196

197 **Climate** We use a simple representation for the climate system with a lin-
 198 ear formula linking temperature change to the stock of carbon emissions [23].
 199 This approach avoids overestimating the delay between emissions and temper-
 200 ature rise. Indeed, the link between cumulative emissions and temperature has
 201 been shown to be almost independent of time and emissions pathways except
 202 for very high emission pathways [35] such as the RCP 8.5: it should thus hold
 203 for any reasonable optimal policy scenario. Emissions are derived from out-
 204 put: $E_t = \sigma_t Y_t(1 - \mu_t)$, where σ_t is the carbon content of production that
 205 decreases exogenously over time. Emissions increase carbon concentration in
 206 the atmosphere and there is no decay. Equation for temperature change is:

207 $T_t = \psi \left(CE_0 + \sum_{s=0}^t E_s \right) = \psi S_t$ where T_t is the global temperature increase
 208 (in comparison with the pre-industrial era) at time t , CE_0 is cumulated emis-
 209 sions up to the first period of the model, E_s the emissions at time s , S_t the
 210 carbon stock in the atmosphere at time t and ψ the transient climate response
 211 to cumulative carbon emissions (TCRE, $\psi = 1.65^\circ\text{C}$ per TtC, according to
 212 Masson-Delmotte et al. [38]).

213

214 **Tipping risk** We model one stylized endogenous tipping point that may de-
 215 crease the output via an increase in the damage factor affecting the productivity.
 216 The tipping point is endogenous as its probability of occurrence is a function of
 217 global average surface temperature. If the tipping point is crossed, the damage
 218 factor Ω faces an irreversible $J\%$ increase. The pre-tipping damage function
 219 writes: $\Omega_1(T) = 1 - \pi T^2$. Once the tipping point is crossed, the damage in-
 220 crease by $J\%$ and the new damage function writes: $\Omega_2(T) = (1 - J)(1 - \pi T^2)$.
 221 The damage occurs with no delay. The probability of tipping is modeled with a
 222 uniform distribution between initial temperature increase with respect to pre-
 223 industrial era and an upper temperature threshold³ to make as few assumptions
 224 as possible about the precise temperature at which a tipping event may occur.
 225 Along the path, this specification allows learnings from the bayesian policy-
 226 maker as she updates her beliefs on the location of the threshold in the state
 227 space and on the probability of tipping at each period. The key assumption
 228 from this specification of the potential tipping event is that there is no tipping
 229 risk if the temperature is stabilized [36]. At each period t , the tipping point is

³The lower bound is the 2015 current excess temperature in comparison with the preindustrial era (0.87°C in 2015). The upper bound is set to 5.7°C according to the upper bound of the temperature increase reached in 2100 in RCP 8.5 [5]. See Appendix E.1 for a sensitivity analysis.

crossed with probability h_t :

$$h_t(T_t, T_{t-1}) = \begin{cases} \frac{T_t - T_{t-1}}{T_{max} - T_{t-1}} & \text{if } T_t < T_{max} \\ 1 & \text{if } T_t \geq T_{max} \end{cases} \quad (3)$$

We have presented above a stochastic model with a stylized tipping point. A second step is to use a social welfare function that allows the study of temporal risk aversion. We present this function in more depth below. To allow comparison with previous literature, we compare how two forms of social preferences behave in a risky intertemporal social setting. The first form is the additive one. The second form is the one of risk-sensitive preferences with positive temporal risk aversion.

2.3. Social preferences

In our model, we write two Bellman equations for the two possible situations, pre- and post-tipping, under the additive and the risk-sensitive social welfare functions, as welfare is affected by a J% increase in the damage factor once the tipping point is crossed. If the tipping point is crossed, the Bellman equation writes the same way for the two programs. The two social welfare functions yield the same policy in the risk-free post-tipping situation: temporal risk aversion plays no role in these risk-free situations, whatever its level. Once the tipping is crossed, all risk is solved: the tipping risk is the sole risk we study here. The state variables of our optimization program are $x_t = (S_t, K_t)$ respectively the cumulative emissions stock and the capital stock at time t. The control variables are $y_t = (\mu_t, s_t)$, respectively the abatement rate and the savings rate at time t. The instantaneous utility function writes: $u_t(x_t, y_t) = C_t^{1-\eta}/(1-\eta)$ with η the elasticity of marginal utility.

Additive preferences Under additive preferences, once the tipping point is crossed, we have: $U_t^{post}(x_t, y_t) = \max_{y_t} [u_t(x_t, y_t) + \beta U_{t+1}^{post}(x_{t+1})]$ under the

constraints: $x_{t+1} = G(x_t, y_{t+1})$ and $y_t \in \Gamma(x_t)$, with Γ the space of possible (positive) values for the control variables and G a transfer function. If the tipping point has not been crossed yet at time t , then it may be crossed at time $t+1$ with probability h_{t+1} or the world can stay in a pre-tipping situation with a probability $(1 - h_{t+1})$. The pre-tipping Bellman equation under additive preferences and under the same constraints as above writes:

$$U_t^{pre}(x_t, y_t) = \max_{y_t} [u_t(x_t, y_t) + \beta[(1 - h_{t+1})U_{t+1}^{pre}(x_{t+1}) + h_{t+1}U_{t+1}^{post}(x_{t+1})]] \quad (4)$$

Risk-sensitive preferences Once the tipping point is crossed, the program under risk-sensitive preferences reduces to the additive one. If $\epsilon = 0$, the program under risk-sensitive preferences reduces to the additive one. Finally, it should be noted that $V^{post} = U^{post}$. The Bellman equation under the same constraints in the pre-tipping situation writes:

$$V_t^{pre}(x_t, y_t) = \max_{y_t} \left(u_t(x_t, y_t) - \frac{\beta}{\epsilon} \ln [(1 - h_{t+1}) \exp(-\epsilon[V_{t+1}^{pre}(x_{t+1})]) + h_{t+1} \exp(-\epsilon[V_{t+1}^{post}(x_{t+1})])] \right) \quad (5)$$

2.4. Comparison with alternative social preferences

We compare the additive expected utility model to risk-sensitive preferences in order to study temporal risk aversion. Two main other frameworks have been used to study risk aversion under endogenous catastrophic climate change: the Epstein-Zin-Weil framework (hereafter, EZW) and the multiplicative preferences.

2.4.1. Epstein-Zin-Weil preferences

EZW preferences have been widely used in risky intertemporal settings to discuss optimal policy, e.g. in Cai and Lontzek [19], because of their flexibility, which allows to disentangle preference over time and preference over states of the world. We depart from it for two main reasons.

The first reason is that these preferences are monotone with respect to first-

281 order stochastic dominance⁴ [13] only in the limit cases where relative risk aver-
 282 sion equals the inverse of the elasticity of intertemporal substitution (they re-
 283 duce to the standard additive model) or when the elasticity of intertemporal
 284 substitution equals one (EZW preferences are then risk-sensitive). If EZW pref-
 285 erences are well ordered in terms of risk aversion ‘in the large’ (willingness to
 286 pay to eliminate all risks), those preferences are not well ordered in terms of risk
 287 aversion ‘in the small’ (willingness to pay for marginal risk reductions). Thus,
 288 a social planner under EZW preferences might choose dominated strategies in
 289 social settings where it is not possible or optimal to eliminate all risk which
 290 may precisely be the case with climate change. In particular, it has been shown
 291 in the theoretical and applied literature that this non-monotonicity can lead to
 292 two types of counter-intuitive behaviours. On the one hand, the EZW agent
 293 can make more precautionary choices than necessary, choosing to build up more
 294 precautionary savings in a risky situation than the savings chosen in the worst
 295 state of the world that could occur under this risk if it happened determinis-
 296 tically [13]. This leads to a more extreme behavior than a max-min approach.
 297 On the other hand, the role of risk aversion could be non-monotone, meaning
 298 that for a higher relative risk aversion and the same risk, the planner can be
 299 less precautionous [32, 15]. The fact that such dominated strategies can be cho-
 300 sen, even if not always, makes this criterion less appealing for the definition of
 301 the optimal policy. Unlike the EZW framework, risk-sensitive preferences are
 302 monotone with respect to first-order stochastic dominance, which means that
 303 dominated strategies are never chosen. In particular, in our setting, we show
 304 in annex [Appendix C](#) that the risk premium is always positive and increasing

⁴A social planner has preferences that respect first-order dominance if, for two lotteries A and B with A dominating B, she prefers A to B regardless of her utility function, as long as it is weakly increasing. The lottery A dominates B if it gives more wealth than B realization by realization.

in the temporal risk aversion ϵ . When relative risk aversion is lower than the inverse of the elasticity of intertemporal substitution, EZW preferences show preference for late resolution of uncertainty and a negative risk premium, while risk-sensitive preferences exhibit preference for early resolution of uncertainty whenever $\epsilon > 0$. Risk-sensitive preferences thus allow a more rational social choice while preserving the flexibility and recursivity properties of the Kreps and Porteus [33] framework.

The second reason why we use risk-sensitive preferences rather than EZW preferences is that the coefficient of relative risk aversion studied in EZW preferences does not directly compare with the absolute risk aversion with respect to intertemporal utility studied under risk-sensitive preferences⁵ as a reduction in relative risk does not always come with a reduction in aggregate risk [12]. A relative risk averse agent prefers to have non-extreme payoffs across states of the world within periods, while a temporally risk-averse planner prefers to have non-extreme payoffs across states of the world over the whole time horizon considered.

2.4.2. Multiplicative preferences

The second form are the multiplicative preferences [14] that rule out pure time preference so that different generations are not given different utility weights because they were born at different dates. Instead, we use an intermediate form

⁵Risk-sensitive preferences use a constant *absolute* risk aversion certainty equivalent, whereas EZW preferences use a constant *relative* risk aversion certainty equivalent [14]. When comparing temporal lotteries of consumption, constant absolute risk aversion has been seen as unrealistic because risk aversion is the same for all levels of wealth under this assumption. Here, the constant absolute risk aversion certainty equivalent is applied to distributions of utility levels rather than consumption levels. This assumption is made under risk-sensitive preferences as monotonicity implies that risk aversion is considered with respect to aggregate utility. Thus, in order to preserve history independence, constant absolute risk aversion with respect to aggregate intertemporal risk ensures that the utility of the first periods does not impact social choice afterwards [13].

326 of risk-sensitive preferences that does not assume away time discounting for
 327 three reasons. Firstly, we do not include an extinction risk, so that without
 328 pure time preference, our undiscounted dynamic program would be too sensi-
 329 tive to the arbitrary terminal value and limit the comparability between the two
 330 programs. The second reason is that we want to analyze the sole role of tempo-
 331 ral risk aversion on social choice rather than intertwining this questioning with
 332 the debate between discounted and undiscounted utilitarianism [47, 40]. The
 333 third reason is the comparability between additive and risk-sensitive preferences.
 334 Indeed, additive and risk-sensitive social planners have the same rankings over
 335 deterministic consumption paths regardless of the value of the temporal risk
 336 aversion ϵ . We can therefore simply vary ϵ within a reasonable value range and
 337 make comparisons between the two social choice criteria under risk for different
 338 values of ϵ .

339 We have characterized the additive and the risk-sensitive social welfare func-
 340 tions and explained how temporal risk aversion can be an important determi-
 341 nant of climate policy. We now assess analytically the impact of temporal risk
 342 aversion on optimal climate policy under a tipping risk.

343 **3. How does temporal risk aversion affect optimal policy under a** 344 **tipping risk?**

345 Firstly, we derive analytically the impact of temporal risk aversion on the
 346 optimal policy under a tipping risk. We decompose the pre-tipping value func-
 347 tions (4) and (5) which incorporate the risk of tipping and analyze the case
 348 where a single state variable determines the chance of crossing the threshold.
 349 We focus solely on S_t , the cumulated stock of emissions at time t . As we are
 350 considering optimal climate policy, we focus on the abatement rate μ_t and derive
 351 the first-order condition of our policy programs. Our analytical decomposition
 352 is a two-step procedure. First, we decompose the immediate short-term effect

on next-period welfare of a marginal variation in abatement rate departing from the optimum, following Lemoine and Traeger [36]. Then, we derive the complete long-term effect of a marginal variation in the cumulative emissions stock on all future probabilities of tipping. The decomposition is done for the additive and risk-sensitive preferences: thus, we can derive how the channels through which a tipping risk affects optimal policy under additive preferences adjust to temporal risk aversion, in both the short and long term.

From the first-order condition of our policy programs, we show that the tipping risk affects optimal policy through three short-term channels. The first channel, the marginal hazard effect *mhe*, measures the impact of the control variable on the immediate probability of tipping. The second channel, the differential welfare impact *dwi*, measures the differential impact of the control variable on welfare depending on the situation, i.e. pre- or post-tipping, and if the tipping point is crossed. The last channel, the marginal impact pre-tipping *mpre*, defines the decrease in next-period's welfare resulting from an increase in the abatement policy if the tipping point has not been crossed yet: possible future tipping points are included in this last channel. Removing all arguments that are independent of μ_t in equation (3), the value of the optimal policy program in the pre-tipping situation under additive preferences writes:

$$u_t[\mu_t^*] + \beta \underbrace{[h_{t+1}(\mu_t^*)U_{t+1}^{post}(\mu_t^*) + (1 - h_{t+1}(\mu_t^*))U_{t+1}^{pre}(\mu_t^*)]}_{U_{t+1}^{eff}} \quad (6)$$

The first term of equation (8) corresponds to the level of instantaneous utility at time t for an optimal choice of the control variable μ_t^* . The second term gives the expected welfare at time t+1 when there is a probability of tipping point under temporal risk neutrality and for an optimal choice of the control variable, scaled by the discount factor β . Varying μ_t gives us the immediate

379 decomposition under additive preferences characterizing optimal policy: $u'_t =$
 380 $\beta(dw_{t+1}^{add} + mhe_{t+1}^{add} + mpre_{t+1}^{add})$, with the following channels:

$$381 \quad \begin{cases} mhe_{t+1}^{add} = \frac{\partial h_{t+1}}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial \mu_t} (U_{t+1}^{pre} - U_{t+1}^{post}) \\ dw_{t+1}^{add} = h_{t+1} \frac{\partial S_{t+1}}{\partial \mu_t} \left(\frac{\partial U_{t+1}^{pre}}{\partial S_{t+1}} - \frac{\partial U_{t+1}^{post}}{\partial S_{t+1}} \right) \\ mpre_{t+1}^{add} = -\frac{\partial U_{t+1}^{pre}}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial \mu_t} \end{cases} \quad (7)$$

382 The risk-sensitive social planner maximizes at time t a utility function V_t
 383 which is linked to the random continuation utility V_{t+1} through the following
 384 recursion: $V_t = u_t + \beta\phi^{-1}(\mathbb{E}[\phi(V_{t+1})])$. The function ϕ writes $\phi(V) = (1 -$
 385 $\exp(-\epsilon V))/\epsilon$. It is increasing and strictly concave for any $\epsilon > 0$. The value
 386 of the optimal policy program in the pre-tipping situation under risk-sensitive
 387 preferences is:

$$388 \quad u_t[\mu_t^*] + \beta \underbrace{\phi^{-1} [h_{t+1}(\mu_t^*)\phi(V_{t+1}^{post}(\mu_t^*)) + (1 - h_{t+1}(\mu_t^*))\phi(V_{t+1}^{pre}(\mu_t^*))]}_{V_{t+1}^{eff}} \quad (8)$$

389 The immediate decomposition under risk-sensitive preferences writes: $u'_t =$
 390 $\beta(dw_{t+1}^{rs} + mhe_{t+1}^{rs} + mpre_{t+1}^{rs})$, with the following channels:

$$391 \quad \begin{cases} mhe_{t+1}^{rs} = \frac{B_{t+1}}{\epsilon} \left(\frac{\partial h_{t+1}}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial \mu_t} [\exp(-\epsilon V_{t+1}^{post}) - \exp(-\epsilon V_{t+1}^{pre})] \right) \\ dw_{t+1}^{rs} = B_{t+1} \left(h_{t+1} \frac{\partial S_{t+1}}{\partial \mu_t} \left[\frac{\partial V_{t+1}^{pre}}{\partial S_{t+1}} \exp(-\epsilon V_{t+1}^{pre}) - \frac{\partial V_{t+1}^{post}}{\partial S_{t+1}} \exp(-\epsilon V_{t+1}^{post}) \right] \right) \\ mpre_{t+1}^{rs} = -B_{t+1} \left(\frac{\partial V_{t+1}^{pre}}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial \mu_t} \exp(-\epsilon V_{t+1}^{pre}) \right) \\ \text{with } B_{t+1} = ((1 - h_{t+1})\exp(-\epsilon V_{t+1}^{pre}) + h_{t+1}\exp(-\epsilon V_{t+1}^{post}))^{-1} \end{cases} \quad (9)$$

392 We highlight how temporal risk aversion implies an adjustment on these
 393 channels in comparison with additive temporally risk-neutral preferences. We
 394 extend the reasoning of Lemoine and Traeger [37] under uncertainty and ambi-
 395 guity aversion to a related setting with risk and risk-sensitive preferences⁶ and

⁶They use an isoelastic function for the transformation with uncertainty aversion in a setting with an ambiguous tipping point. The equivalent of risk-sensitive preferences in an

use their general approximations for the adjustments on the channels implied by a concave transformation of the additive social welfare function under a tipping risk. The complete procedure is depicted in [Appendix A](#). The measure of absolute temporal risk aversion $\left. \frac{-\phi''}{\phi'} \right|_{V^{eff}}$ is equal to ϵ . We adjust the temporally risk-neutral marginal hazard effect channel mhe^{add} obtained from additive preferences to find the risk-sensitive marginal hazard effect mhe^{rs} :

$$mhe^{rs} \approx mhe^{add} \left[1 + \epsilon \left(V^{eff} - \frac{V^{pre} + V^{post}}{2} \right) \right] \quad (10a)$$

where V^{post} is the continuation value if the tipping point has already been crossed, V^{pre} the continuation value if the tipping point has not been crossed yet and V^{eff} the random continuation value for an optimal choice of the policy variable. The amplitude and the sign of the adjustment can not be derived analytically. Indeed, an increase in temporal risk aversion ϵ is counter-balanced by its negative impact on V^{eff} as V^{eff} is decreasing in ϵ . In comparison with the arithmetic mean $(V^{pre} + V^{post})/2$, the two possible regimes in V^{eff} are weighted by the probability of (not) tipping, lower (higher) than one half in any optimal policy paths considered here. We thus expect the marginal hazard effect to be increasing with ϵ in our setting. The marginal hazard effect, depicting the marginal impact of a marginal increase in abatement on the immediate probability of tipping, relates to the social value of catastrophic risk reduction [\[14\]](#) and the VSL-like parameter of Weitzman [\[53\]](#). This channel is associated with self-protection in Lemoine and Traeger [\[36\]](#).

We then adjust [\[7\]](#) the temporally risk-neutral differential welfare impact dwi^{add} to obtain the risk-sensitive differential welfare impact dwi^{rs} . This channel is de-

uncertain setting would be the multiplier criterion [\[13\]](#).

⁷Taken from [\[37\]](#), the approximation holds for a low shock.

420 pictured as self-insurance in Lemoine and Traeger [36]. The adjustment writes:

421

$$422 \quad dwi^{rs} \approx dwi^{add} + \epsilon h \left[(V^{eff} - V^{pre}) \left(\frac{\partial V^{pre}}{\partial \mu} \right) - (V^{eff} - V^{post}) \left(\frac{\partial V^{post}}{\partial \mu} \right) \right] \quad (10b)$$

423 Similarly, the sign of the adjustment of temporal risk aversion on the risk-
 424 neutral DWI cannot be determined analytically. An increase in the temporal
 425 risk aversion ϵ decreases V^{eff} and both terms in the bracket, so that the overall
 426 sign depends on the relative level of the marginal welfare impact of the change
 427 in policy variable in the pre-threshold and the post-threshold worlds as in the
 428 temporally risk-neutral case. The adjustment decreases with the probability of
 429 tipping. We expect this channel and the adjustment to be negligible. Indeed,
 430 they depend on the value and the trajectory of the tipping probability with
 431 respect to ϵ . But the larger ϵ is, the lower the probability of tipping, because
 432 optimal policy under large temporal risk aversion is expected to be stricter. In
 433 our specification as in Lemoine and Traeger [36, 37], the dwi might be com-
 434 pletely overwhelmed by the mhe .

435

436 One can finally adjust the last channel: the direct impact of the change in
 437 policy variable on the welfare if one stays in a pre-tipping situation in the next
 438 period:

$$439 \quad mpre^{rs} = mpre^{add} \frac{\phi'(V^{pre})}{\phi'(V^{eff})} \quad (10c)$$

440 The adjustment implied by temporal risk aversion is the relative slope of the
 441 transformed continuation value if we stay in a pre-tipping situation on the slope
 442 of the transformed random continuation value. The size of the adjustment de-
 443 pends on the concavity of ϕ , i.e., the strength of temporal risk aversion ϵ . This
 444 term is equal to one when there is no tipping risk, i.e. if the temperature is sta-
 445 bilized, and goes to 0 if the probability of tipping h increases. The adjustment
 446 implied by temporal risk aversion decreases $mpre$ unambiguously as $V_{pre} > V_{eff}$.

447

448 We have focused on the immediate impact of a marginal variation of the
 449 policy variable around the optimum and identified the channels through which
 450 the tipping risk affect next-period welfare under additive and risk-sensitive pref-
 451 erences. So far, we have only analyzed the immediate channels (*mhe* and *dwi*)
 452 and left all future impacts of a marginal change in the policy variable in the
 453 pre-tipping continuation value included in *mpre* as in Lemoine and Traeger [37].
 454 Indeed, today's emissions also affect all future probabilities of triggering the
 455 tipping point. In order to recover the full impact of temporal risk aversion on
 456 the optimal policy under a tipping risk, we need to decompose further this *mpre*
 457 channel. We do not focus on the marginal impact of an increase in a control vari-
 458 able (i.e. the abatement rate), but on the marginal impact on the pre-tipping
 459 value function of a marginal increase in a state variable (the concentration stock
 460 *S*). As we assume that there is no decay, a marginal increase in the concentration
 461 stock can be analyzed as a marginal increase in carbon emissions. As in Jensen
 462 and Traeger [30], we assume that the dynamic system is well-defined so that the
 463 shadow value of the carbon concentration increase $\partial V^{pre}/\partial S$ grows sufficiently
 464 slowly along the optimal path to make the limit approach zero over our large
 465 time horizon. We can advance the derivative of our pre-tipping value function
 466 with respect to emissions by one period and reinsert it in itself:

$$467 \quad \frac{\partial V_t^{pre}}{\partial S_t} = u'_t - \beta \left(mhe_{t+1}^{rs} + dwi_{t+1}^{rs} - B_{t+1} \exp(-\epsilon V_{t+1}^{pre}) \left[u'_{t+1} - \beta (mhe_{t+2}^{rs} + dwi_{t+2}^{rs} - B_{t+2} \exp(-\epsilon V_{t+2}^{pre}) \frac{\partial V_{t+2}^{pre}}{\partial S_{t+2}}) \right] \right) \quad (11)$$

468 Iterating the procedure eventually yields a general expression of the marginal
 469 impact of a marginal increase in carbon emissions on all present and future
 470 periods. The complete decomposition under risk-sensitive preferences writes:

$$471 \quad \frac{\partial V_t^{pre}}{\partial S_t} = u'_t - \beta [mhe_{t+1}^{rs} + dwi_{t+1}^{rs}] + \sum_{i=t+1}^{\infty} \beta^{i-t} \left(\prod_{k=t+1}^i \underbrace{\frac{\phi'(V_k^{pre})}{\phi'(V_k^{eff})}}_{\text{adjustment}(mpre)} \right) (u'_i - \beta [mhe_{i+1}^{rs} + dwi_{i+1}^{rs}]) \quad (12)$$

472 The *mpre* channel of the immediate decomposition disappears. To differentiate
 473 them from the immediate decomposition terms, the full decomposition terms are
 474 in capital letters. The complete decomposition $\partial V_t^{pre}/\partial S_t = U'_t - MHE_t^{rs} -$
 475 DWI_t^{rs} now includes all present and future effects:

$$476 \quad \begin{cases} U'_t = u'_t + \sum_{i=t+1}^{\infty} \beta^{i-t} \left(\prod_{k=t+1}^i \frac{\phi'(V_k^{pre})}{\phi'(V_k^{eff})} \right) u'_i \\ MHE_t^{rs} = \beta mhe_{t+1}^{rs} + \sum_{i=t+1}^{\infty} \beta^{i-t+1} \left(\prod_{k=t+1}^i \frac{\phi'(V_k^{pre})}{\phi'(V_k^{eff})} \right) mhe_{i+1}^{rs} \\ DWI_t^{rs} = \beta dwi_{t+1}^{rs} + \sum_{i=t+1}^{\infty} \beta^{i-t+1} \left(\prod_{k=t+1}^i \frac{\phi'(V_k^{pre})}{\phi'(V_k^{eff})} \right) dwi_{i+1}^{rs} \end{cases} \quad (13)$$

477 The complete MHE^{rs} and DWI^{rs} depend on the sign and amplitude of all
 478 the present and future immediate mhe^{rs} and dwi^{rs} , and all future effects are
 479 scaled by the discount factor and the positive adjustment implied by temporal
 480 risk aversion. We have described analytically how temporal risk aversion changes
 481 the various channels through which a tipping risk affects a decision-maker, both
 482 short and long term. We assess numerically the impact of temporal risk aver-
 483 sion in a dynamic climate-economy stochastic model under a tipping risk and
 484 quantify the different channels depicted.

485 4. A numerical investigation

486 4.1. Calibration

487 We use the same specifications for the macroeconomic model as Nordhaus
 488 [39]. We use typical ranges of possible values for the key parameters. The pure
 489 rate of time preference ρ is 1.5% [39]. The marginal utility parameter η is set
 490 to 1.5 with a sensitivity analysis from 0.5 to 2.5. We explore a large range for
 491 the shock J, ranging from 0 to 10% as explored in van der Ploeg and de Zeeuw
 492 [51], Cai and Lontzek [19] and van der Ploeg and de Zeeuw [52].

493 Social planners under additive and risk-sensitive preferences have the same
 494 ordering over deterministic consumption paths⁸. Thus, we can make compar-

⁸On the contrary, this is not the case for all values of ϵ under multiplicative preferences that

495 isons between the two social choice criteria under risk for different values of ϵ .
 496 We look for a range of plausible values for this parameter and a benchmark value
 497 within it to set a default value and perform a sensitivity analysis. The range of
 498 values used in the literature is large. Anderson [4] uses 0.1, 1 and 2 to study the
 499 dynamics of optimal Pareto allocations of risk-sensitive agents. When studying
 500 precautionary savings, Bommier et al. [13] explore large values ranging from 0
 501 to 4, and Bommier and Le Grand [15] explore very large values, up to 100. In
 502 order to reduce the plausible range, we use the fact that, when the elasticity of
 503 intertemporal substitution is set to one, the EZW preferences are risk-sensitive
 504 preferences [49]. Indeed, risk-sensitive and EZW preferences are special cases
 505 of the more general family of recursive Kreps and Porteus [33] preferences. An
 506 analytical relation between the temporal risk aversion on the one hand and pure
 507 time preference ρ and relative risk aversion χ of EZW preferences on the other
 508 hand can thus be formulated in this precise case: $\epsilon = -(1 - \beta)(1 - \chi)$ with χ the
 509 coefficient of relative risk aversion with respect to atemporal wealth gambles,
 510 and β the discount rate. Following the IAM literature calibration for χ [1, 19],
 511 we use $\chi = 10$ as a benchmark and run a sensitivity analysis around this value.
 512 In our benchmark case, with $\chi = 10$ and $\rho = 1.5\%$ yearly, we have $\epsilon = 0.133$.
 513 A low $\chi = 1.1$ would yield $\epsilon = 0.0015$ while a large $\chi = 20$ would yield $\epsilon = 0.3$.
 514 The lower the pure time preference, the lower the difference between additive
 515 and risk-sensitive preferences [14]. Our benchmark measure may not be adapted
 516 to social settings : a welfare-maximizing social planner might be more tempo-
 517 rally risk averse than individuals when a catastrophic and irreversible risk bears
 518 on all future generations. In an empirical elicitation of the aversion towards

are undiscounted ($\rho = 0$). Thus, Bommier et al. [14] have to rely on a specific calibration of ϵ so
 that additive and multiplicative preferences yield the same discount rate and are comparable.
 The calibration of ϵ under multiplicative preferences depends on the form of the instantaneous
 utility, the level of pure time preference and the post-tipping exogenous consumption.

519 correlated risks in the context of donations to risky aid projects, Gangadharan
520 et al. [27] find that individuals are more averse to correlated risks when they
521 donate other people’s money. This is an interesting line of thought for climate
522 change, where the contemporary social planner has to choose an appropriate
523 level of temporal risk aversion for other generations than the one he belongs to.
524 Thus, our benchmark value for the temporal risk aversion is conservative and
525 in the lower bound of those estimates.

526 4.2. A comparison of the two social welfare functions under risk

527 We derive the optimal climate policy under the two social welfare functions
528 in a risky intertemporal social setting using dynamic programming. Details of
529 the resolution are in Appendix B. A key instrument to compare optimal policy
530 along the trajectory is the social cost of carbon (SCC) at initial time. For both
531 specifications, it writes: $-\beta(\partial_S \mathbb{E}[W_1]|_{y_1} / \partial_C W_0|_{x_0, y_0^*})$ with y_0^* the optimal
532 abatement and investment of the program at initial time given x_0 and β the
533 discount rate derived from pure time preference. W , the value function, can be
534 U (additive) or V (risk-sensitive). Figure 1 gives the absolute value of the SCC
535 (\$/tC) under additive and risk-sensitive preferences at initial time for a range
536 of irreversible increase in the damage factor J and the ratio of the SCC under
537 risk-sensitive preferences to the SCC under additive preferences for various ϵ
538 and J .

539 We can draw three conclusions from the graphs above. First, optimal cli-
540 mate policy under risk-sensitive preferences is more stringent for any value of
541 ϵ and J than under additive preferences. An increase in temporal risk aversion
542 unambiguously leads to an increase in the social cost of carbon due to the mono-
543 tonicity of risk-sensitive preferences. The second conclusion is that switching
544 from additive to risk-sensitive preferences under a tipping risk induces a large
545 change in optimal policy: the form of the social welfare function matters, as

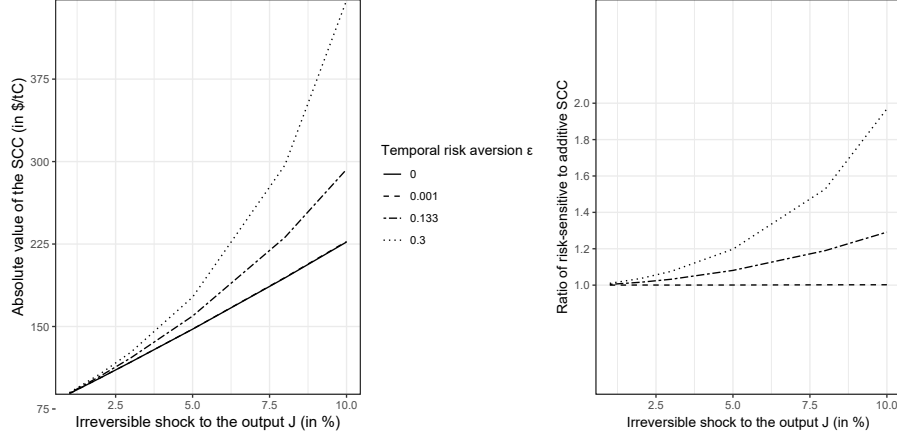


Figure 1: Absolute values of the additive and risk-sensitive SCC (in \$ per tC) at initial time (left) and ratio of the risk-sensitive SCC to the additive SCC (right) for various J and ϵ under our benchmark calibration ($\eta = 1.5$, $\rho = 1.5\%$). The curves overlap for the two smallest values of ϵ in the left-hand graph. Same graphs with a wider range for J are given in [Appendix E.1](#)

546 already highlighted in Bommier et al. [\[14\]](#) for more catastrophic collapses. For
547 a tipping point inducing a 10% irreversible increase in the damage factor, the
548 SCC under risk-sensitive preferences is 30% higher than under additive prefer-
549 ences under our benchmark $\epsilon = 0.133$: it goes from 227\$ per tC to 293\$ per
550 tC. This difference is increasing with the size of the possible shock J: the larger
551 the tipping risk, the larger the difference between the optimal policies. Finally,
552 temporal risk aversion plays a key role: under risk-sensitive preferences, for the
553 largest $\epsilon = 0.3$, the SCC at initial time is 2-times higher than under additive
554 preferences for a 10% shock. The slope of the ratio of the risk-sensitive SCC
555 to the additive SCC is also increasing with ϵ . Increasing temporal risk aversion
556 increases unambiguously the weights attributed to the catastrophic states of
557 the world where numerous generations are badly off with a low intertemporal
558 utility level. We run a sensitivity analysis in [Appendix E.3](#) to check if our result
559 is not affected by the calibration of the inequality aversion parameter η . The
560 ratio of the risk-sensitive to the additive SCC is increasing in the value of the

inequality aversion η . The SCC under risk-sensitive preferences is larger than under additive preferences for any value of η explored here.

To illustrate the magnitude of the change in optimal climate policy arising from temporal risk aversion, we show how switching from additive to risk-sensitive preferences compares with changes in the value of some parameters under additive preferences. We focus on two parameters that have been subject to debates in the literature. On the one hand, we consider the rate of pure time preference ρ [47, 40]. On the other hand, we focus on the value of the economic damage generated by climate change [41], and more specifically by a climate tipping point. First, Figure 2 (left) shows how a change from additive to risk-sensitive preferences compares to a change in ρ under additive preferences. Switching from additive to risk-sensitive preferences under a 10% tipping risk and for our benchmark calibration of the temporal risk aversion ($\epsilon = 0.133$) is equivalent to a 50% decrease in the value of ρ under additive preferences. In other words, the optimal policy derived from risk-sensitive preferences for our benchmark calibration ($\epsilon = 0.133$, $\eta = 1.5$, $\rho = 1.5\%$) and under a 10% tipping risk is obtained under additive preferences when $\rho = 1\%$ other things being equal. Figure 2 (right) shows that it takes a 14% shock for the additive preferences to give the same SCC as for a 10% irreversible increase in the damage factor under risk-sensitive preferences. The difference between the two approaches becomes more pronounced as the level of risk intensifies.

The numerical estimation of the channels analytically depicted in section (3) provides an understanding of the channels through which a tipping risk affects a temporally risk-averse planner. In our analytical decomposition, we firstly derived the channels through which a marginal increase in the policy variable departing from the optimum affects welfare in the next period under a tipping

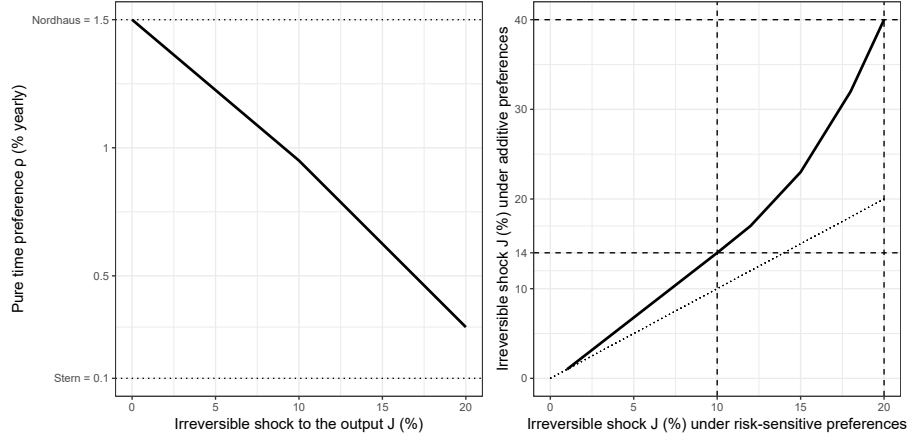


Figure 2: Equivalence in ρ (left) and J (right) needed to obtain the same SCC at initial time under additive and risk-sensitive preferences under our benchmark calibration. On the left, we represent the pure time preference (ρ) that is needed under additive preference (all else being equal) to match the risk-sensitive SCC for various J . On the right, we represent the irreversible shock J that is needed under additive preference (all else being equal) to match the risk-sensitive SCC for various J . The dotted line from the right-hand graph is the identity function.

588 risk and for a risk-sensitive planner. Thus, we have left aside all the future
589 impacts on subsequent periods in this immediate decomposition, in particular
590 the impact of the change in the policy variable on all future probabilities of
591 crossing the threshold. Then, we have performed a full decomposition to take
592 into account the impact of this change in policy on welfare in all future periods:
593 this is the complete decomposition. We have shown that there are two channels
594 through which tipping risk can influence optimal policy: the marginal hazard
595 effect (immediate and complete) and the differential welfare impact (immediate
596 and complete). We now run a numerical estimation of these channels to un-
597 derstand how temporal risk aversion may affect the channels through which the
598 tipping risk affects the planner.

599 We can draw two conclusions from Figure 3. First, we see from our numerical
600 estimation that the main channel is the marginal hazard effect. Indeed, the
601 planner is ready to give up welfare in order to reduce all present (immediate)

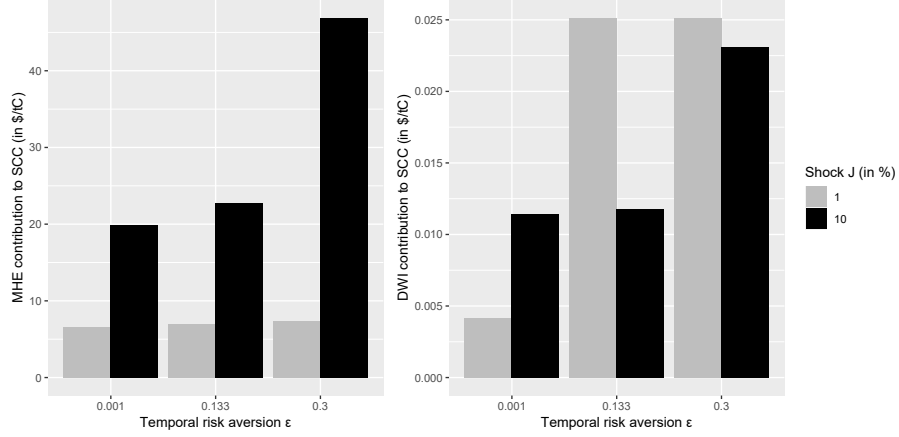


Figure 3: The graphs give the marginal contributions to the SCC at initial time (in \$) of the complete *MHE* (left) and the complete *DWI* (right) under risk-sensitive preferences for various J and ϵ . The scales for the two graphs are different because the two channels are several orders of magnitude apart. We give the same graphs for the immediate decomposition in [Appendix E.4](#)

and future (complete) probabilities of crossing the threshold. This is partly due to the setting generally chosen in the literature to represent tipping points, as we do not model adaptation as an endogenous choice, which could for example decrease the level of damage J . Whether some form of adaptation can decrease the damage of such regime shifts remains uncertain, thus justifying its exclusion from our framework. The second conclusion from the numerical estimation is that the marginal hazard effect channel is increasing in the possible shock and in temporal risk aversion. A higher temporal risk aversion increases the stringency of the optimal policy, as highlighted above, and decreases even further the relative weight of the differential welfare impact in comparison with the marginal hazard effect.

5. Discussion

We study analytically and numerically in an integrated model with a stochastic tipping risk the role of absolute risk aversion with respect to intertemporal

616 utility, i.e. temporal risk aversion. We compare the optimal climate policy
617 arising from the expected discounted utility model to a risk-sensitive social wel-
618 fare function exhibiting temporal risk aversion. A temporally risk-averse social
619 planner maximising the welfare of successive generations prefers to lower the
620 possibility of an irreversible damage bearing on all subsequent generations. In
621 this sense, she adopts a social risk diversification strategy to hedge against po-
622 tential environmental regime shifts.

623 First, while the two social welfare functions yield the same optimal climate
624 policy in a risk-free setting, they differ once a tipping risk is introduced. As-
625 sumptions regarding the structure of the social welfare function appear as least
626 as important as the debated value of some parameters in the expected utility
627 model, such as the damage from a tipping point or the value of pure time pref-
628 erence. It should be emphasized that the assumption of temporal risk neutrality
629 embedded in expected utility, while justifiable in risk-free models with smooth
630 climate change, may not adequately capture possible non-linearities and abrupt
631 regime changes in the climate system, which have been extensively documented
632 in climate science [\[5\]](#). Ignoring temporal risk aversion may lead to underesti-
633 mating the severity of climate risks and result in more lenient climate policies.
634 Therefore, considering temporal risk aversion becomes crucial when studying
635 correlated intertemporal social risks.

636 Second, optimal policy under temporal risk aversion is more stringent than
637 under temporal risk neutrality. The difference between the two social welfare
638 functions increases more than proportionally to the increase in the shock J or
639 the temporal risk aversion ϵ . For a 10% irreversible increase in the damage
640 factor, the SCC under temporal risk aversion is 30% higher than the SCC under
641 risk neutrality under our benchmark calibration. Our key take-away is that
642 if one believes that major catastrophes bearing large multiplier effects such

643 as irreversible regime shifts are possible, the social planner’s aversion towards
644 those risks bearing on intertemporal utility should be accounted for. On the
645 other hand, if there is no such risk or if the possible damage is low, then we
646 should stick to the additive model as it does not come with the ethical drawbacks
647 catastrophe aversion bears.

648 The last conclusion is that optimal climate policy in our setting is mainly
649 driven by the marginal hazard effect. The tipping risk affects optimal policy as
650 the social planner wants to reduce all present and future probabilities of cross-
651 ing the tipping point. This channel is increasing in the possible shock J and
652 increasing in the temporal risk aversion. The risk-sensitive planner is willing to
653 give up more wealth to avoid the catastrophic event.

654

655 Our analysis suffers three main limitations. Firstly, our model, although
656 including a stochastic risk, suffers from the limitations often pointed out in in-
657 tegrated climate-economy models: the specification of the damage function, the
658 exogenous technological change dynamics and the assumptions regarding future
659 growth are for example uncertain. Secondly, our representation of tipping points
660 is limited, as we focus on a single tipping point and do not consider various char-
661 acteristics, such as their probability of occurrence, reversibility, abruptness, and
662 time horizons. Additionally, our tipping probability is solely a function of global
663 temperature, while other drivers, such as deforestation, can also contribute to
664 tipping points. These limitations leave room for further research to provide a
665 more comprehensive and precise representation of climate tipping points and
666 damages. Lastly, our model assumes known probabilities for the tipping risk.
667 Under ambiguity about the tipping points, a temporally risk averse planner
668 might not prefer higher diversification [\[9\]](#).

669 Finally, we do not take any stance on what the *right* social welfare function

670 is. This question remains open to scientific and public debates. In particular,
 671 the risk-sensitive social planner is not an expected utility maximizer. This may
 672 be defensible as one may ‘accept the sure-thing principle for individual choice
 673 but not for social choice, since it seems reasonable for the individual to be
 674 concerned solely with final states while society is also interested in the process
 675 of choice’ [22]. Temporal risk aversion helps us understand the specificity of the
 676 social choice issue climate change raises when it is considered not as a linear and
 677 smooth phenomenon, but as a phenomenon that can give rise to non-linearities
 678 and abrupt regime changes. A future research avenue could be to elicit the
 679 value that individuals would give to this parameter in the context of normative
 680 intergenerational social choice.

681 If our analysis is applied to a stylized climatic tipping risk, we believe that
 682 risk-sensitive preferences and temporal risk aversion might be used for the study
 683 of more standard smooth risks, as long as they are endogenous and correlated.
 684 Indeed, as risk-sensitive preferences exhibit preference for catastrophe avoid-
 685 ance when the social planner has temporal risk aversion, they comply with a
 686 weaker pareto axiom in comparison with additive preferences [16]: this axiom
 687 states that there is no difference between the social planner’s and the individ-
 688 uals’ preferences as long as uncorrelated risks are considered, but that some
 689 divergence may occur when correlated risks are at play. This intertemporal so-
 690 cial choice criterion might thus bear critical implications for the management
 691 of correlated risks, for instance the large aggregate social risks due to potential
 692 ecological thresholds (e.g. biodiversity collapse).

693 Appendix A. Analytic decomposition details

694 We follow Lemoine and Traeger [37] to find an analytic approximation of
 695 how the risk-neutral channels adjust under temporal risk aversion. In addition,
 696 we disentangle mhe from dwi . Starting from expression of mhe^{add} and mhe^{rs}
 697 in equation (7) and (9), we write:

$$698 \quad mhe_{t+1}^{rs} = \frac{\partial h_{t+1}}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial \mu_t} \left(\frac{\phi(V_{t+1}^{pre}) - \phi(V_{t+1}^{post})}{\phi'(V_{t+1}^{eff})} \right) \quad (A.1)$$

699 Thus:

$$700 \quad mhe_{rs} = mhe_{add} \underbrace{\frac{\phi(V^{pre}) - \phi(V^{post})}{\phi'(V^{eff})(V^{pre} - V^{post})}}_{adj_{mhe}} \quad (A.2)$$

701 and recall that $\phi(V) = (1 - \exp(-\epsilon V))/\epsilon$. A second order Taylor expansion
 702 for $\phi(V^i)$ around $\phi(V^{eff})$ gives: $\phi(V^i) \approx \phi(V^{eff}) + \phi'(V^{eff})[V^i - V^{eff}] +$
 703 $\frac{1}{2}\phi''(V^{eff})[V^i - V^{eff}]^2 + O([V^i - V^{eff}]^3)$. We have:

$$704 \quad \phi(V^{pre}) - \phi(V^{post}) \approx \phi'(V^{eff})[\phi(V^{pre}) - \phi(V^{post})] + \frac{1}{2}\phi''(V^{eff})[(V^{pre})^2 - (V^{post})^2 + 2V^{eff}(V^{post} - V^{pre})] \quad (A.3)$$

705 And :

$$706 \quad adj_{mhe} \approx 1 + \frac{-\phi''}{\phi'} \bigg|_{V^{eff}} \left[V^{eff} - \frac{V^{pre} + V^{post}}{2} \right] \quad (A.4)$$

707 This yields our final expression for the adjustment implied by temporal risk
 708 aversion on mhe^{rs} . Expression for dwi^{add} is in equation (7). For dwi^{rs} in
 709 equation (9), we use a more restricted expression than Lemoine and Traeger [37].
 710 Indeed, we exclude mhe from dwi and consider only the differential impact of
 711 a marginal increase in the pre and post tipping if the tipping point is actually
 712 crossed (with probability h). The expression writes:

$$713 \quad dwi_{t+1}^{rs} = h_{t+1} \frac{\partial S_{t+1}}{\partial \mu_t} \left(\frac{\phi'(V^{pre})}{\phi'(V^{eff})} \frac{\partial V_{t+1}^{pre}}{\partial S_{t+1}} - \frac{\phi'(V^{post})}{\phi'(V^{eff})} \frac{\partial V_{t+1}^{post}}{\partial S_{t+1}} \right) \quad (A.5)$$

714 Then, we can write:

$$715 \quad dwi_{t+1}^{rs} = dwi_{t+1}^{add} + h_{t+1} \frac{\partial S_{t+1}}{\partial \mu_t} \left(\left[\frac{\phi'(V^{pre})}{\phi'(V^{eff})} - 1 \right] \frac{\partial V_{t+1}^{pre}}{\partial S_{t+1}} - \left[\frac{\phi'(V^{post})}{\phi'(V^{eff})} - 1 \right] \frac{\partial V_{t+1}^{post}}{\partial S_{t+1}} \right) \quad (\text{A.6})$$

716 We do a first-order approximation of $\phi'(V^i)$ for $i \in \{pre, post\}$ as Lemoine
 717 and Traeger [37], assuming that the tipping point does not cause too large a
 718 welfare loss, to obtain $\frac{\phi'(V^i)}{\phi'(V^{eff})} - 1 \approx \frac{\phi'(V^{eff}) + \phi''(V^{eff})[V^i - V^{eff}]}{\phi'(V^{eff})} - 1 \approx -\epsilon(V^i -$
 719 $V^{eff})$. This approximation, together with equation (A.6), yields equation (10b).
 720 Finally, equation (10c) is derived from equations (7) and (9).

721 Appendix B. Resolution

722 We solve our recursive programs using dynamic programming. For each so-
 723 cial welfare function, we approximate the value function in the post-tipping
 724 world and then in the pre-tipping world using the solution from the post-
 725 threshold problem. We interpolate recursively starting from the last period
 726 and approximate the unknown value functions with Chebyshev polynomials.
 727 We choose a 10^{-3} tolerance for the solver: our result is not affected by stricter
 728 tolerance. In each regime (pre- and post-tipping), the value functions are ex-
 729 pected to be smooth as the tipping risk is the only risk we consider. We use
 730 a four degree complete Chebyshev approximation in the two-dimensional state
 731 space. Additional degrees do not affect the results. The state variables are the
 732 carbon stock in the atmosphere S_t and the stock of capital K_t at time t . The
 733 time-dependent approximation space is defined around a deterministic growth
 734 path derived from Ramsey formula. Once we have interpolated recursively at
 735 each time step, we simulate the optimal path for each control and state vari-
 736 ables starting from the first period. In the stochastic case with a tipping point,
 737 we run 1.000 simulations. An increase in the number of simulations does not
 738 affect significantly the median path. A key element is the definition of a ter-
 739 minal value in the program. The calculation is done on a finite horizon ($T =$

600 years) as an approximation of the infinite program. The terminal value is defined as the sum of all the period utilities from time T to infinity. The assumption made is that the consumption will grow for a constant capital per efficient capita and total abatement, with a deterministic path for the capital derived from Ramsey. The terminal constraint uses a modified discount factor [7]. The choice of the terminal value does not affect the program : a 10% increase in the terminal value does not significantly affect the optimal path. It writes: $TVF = u(\bar{c}) / (1 - \beta(1 + GA))^{\delta(\frac{1-\eta}{1-\alpha})}$ with $\bar{c}$ the consumption for constant capital per efficient capita and total abatement, β the discount rate, δ the time step, η the marginal utility parameter, α the capital elasticity in the production function, and GA the annual growth rate of productivity from the last period.

Appendix C. Risk-sensitive preferences and the risk premium

We show that the risk premium is positive for all ϵ under risk-sensitive preferences. We give the share of the risk-sensitive SCC under expected damages in the risk-sensitive stochastic SCC for various values of ϵ , J and for our benchmark $\eta = 1.5$, following Taconet et al. [48]. In particular, we show numerically on the graph on the left below that the risk premium is positive for all values of ϵ in $\mathbb{R}^+$ under risk-sensitive preferences, unlike for EZW preferences. As some pure risk is already priced under additive preferences with η , we also want to highlight how much the risk premium is increased by temporal risk aversion under our benchmark calibration: we plot on the graph on the right, for different values of ϵ and under a benchmark $J = 10\%$ and $\eta = 1.5$, the share of the additive risk premium in the risk-sensitive risk-premium: $100 * (SCC_{stoch}^{add} - SCC_{ed}^{add}) / (SCC_{stoch}^{rs} - SCC_{ed}^{rs})$. The additive risk premium is always lower than the risk-sensitive risk premium for all $\epsilon \in \mathbb{R}^+$, i.e. when the social planner has temporal risk aversion.

On the graph on the left, we see that the share of expected damages in the

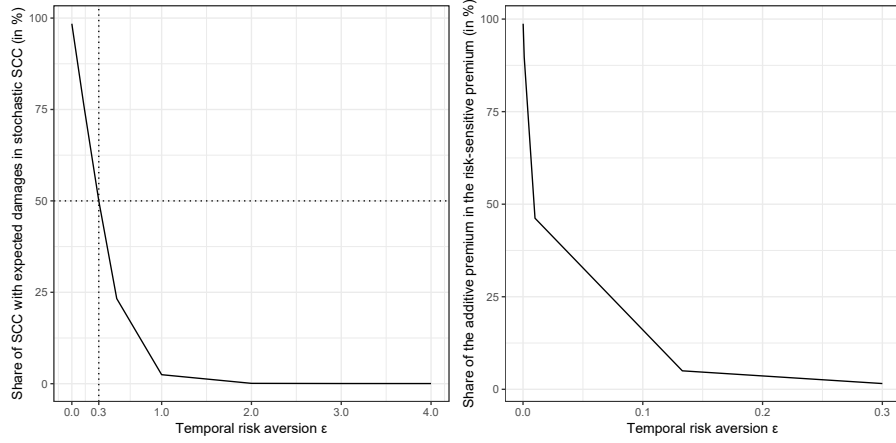


Figure C.4: The graph on the left gives the share of the stochastic SCC that is explained by expected damages (in %). The lowest value explored for ϵ is 0.0001 and the share would converge to 100 for $\epsilon \rightarrow 0$. The graph on the right gives the share of the risk-sensitive risk premium that is already priced under additive preferences. The lowest value explored for ϵ is 0.0001 and the share would converge to 100 for $\epsilon \rightarrow 0$. Both graphs are given for various ϵ and a benchmark $J=10\%$ and $\eta = 1.5$. The two graphs do not have the same scale for ϵ as the share goes quickly to 0 for values above $\epsilon > 0.3$ for the graph on the right

767 stochastic SCC is 50% for $\epsilon = 0.3$. In the remaining 50% of the stochastic SCC
768 that are due to pure risk for $\epsilon = 0.3$, we see on the graph on the right that
769 the pure risk already priced under additive preferences represents around 2% of
770 the risk-sensitive risk premium. Most of the risk premium under risk-sensitive
771 preferences stems from temporal risk aversion.

772 Appendix D. Time paths

773 We provide some time paths for our key variables.

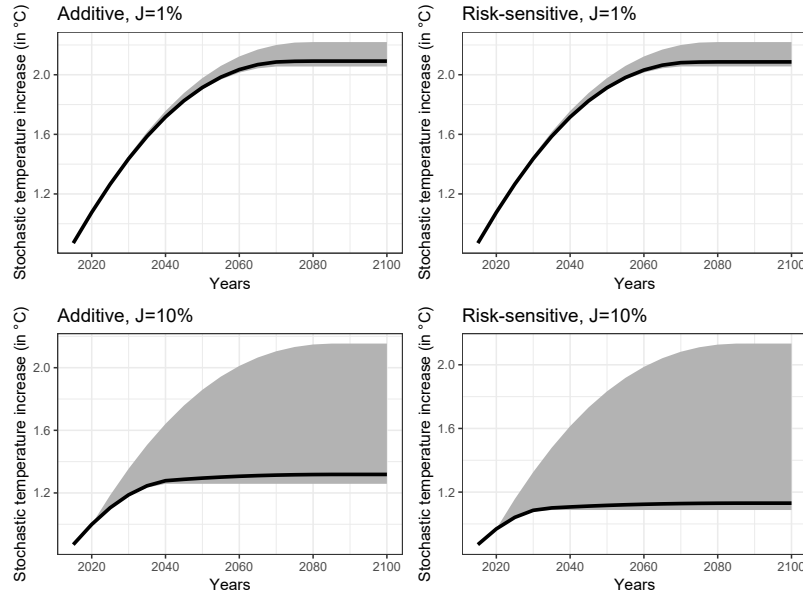


Figure D.5: The graphs give the time paths of the mean temperature increase until 2100 under additive (left) and risk-sensitive (right) preferences, for $J=1\%$ (up) and a $J=10\%$ (down), for $\epsilon = 0.133$. We give the mean (solid line) and $[5\% : 95\%]$ confidence interval (shaded area) over 1.000 stochastic runs.

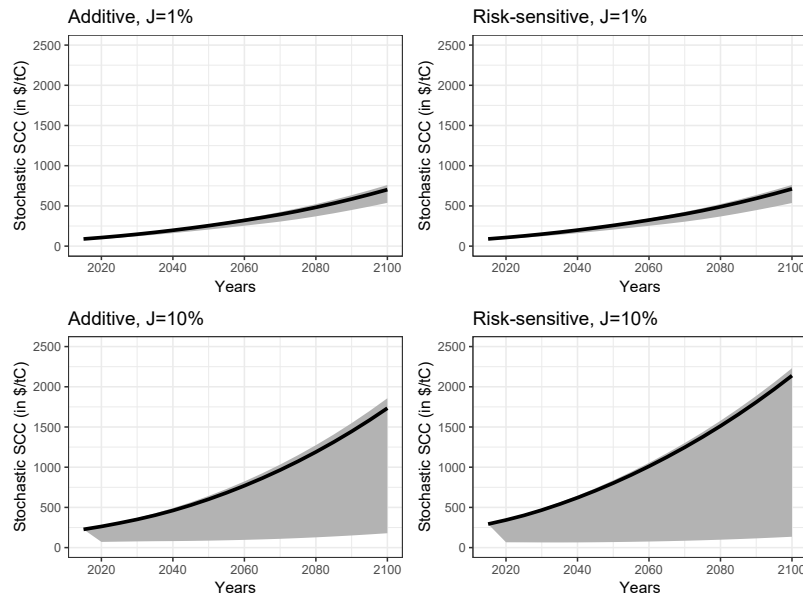


Figure D.6: Same graph as above but with the social cost of carbon.

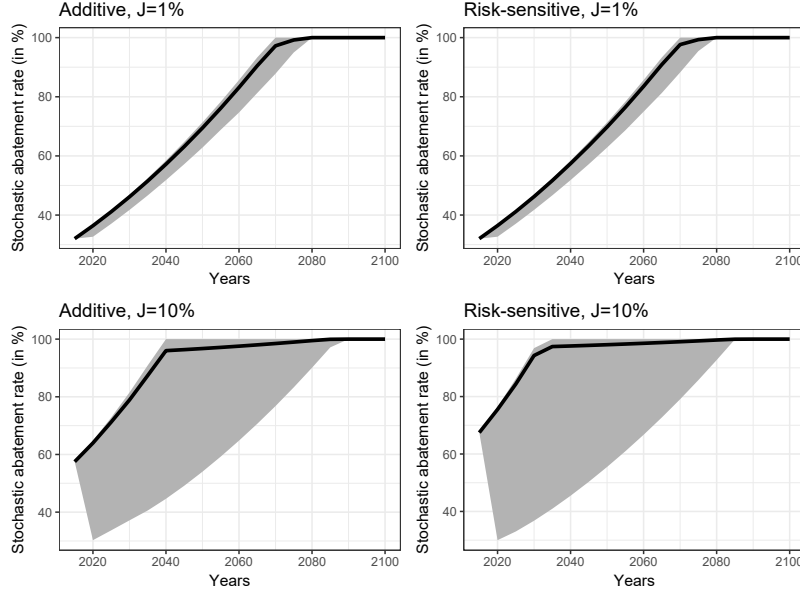


Figure D.7: Same graph as above but with the abatement rate.

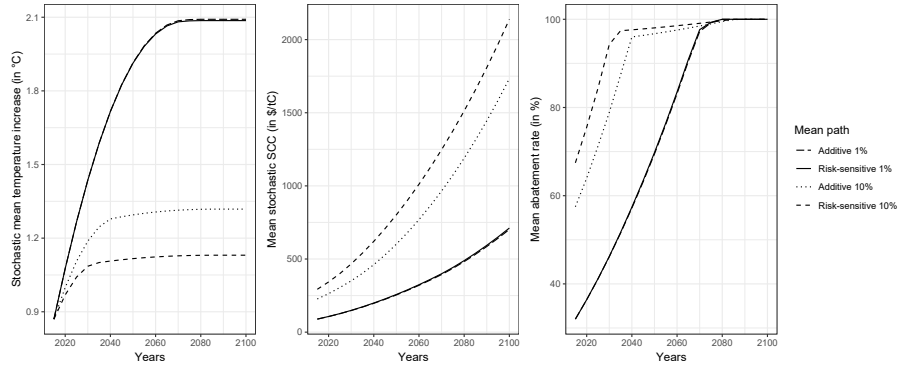


Figure D.8: The graphs give the mean time paths of the temperature increase in $^{\circ}\text{C}$ with respect to preindustrial era (left), the SCC (middle) and the abatement rate (in %) until 2100. In the risk-sensitive case and for $J=10\%$ ($J=1\%$), the tipping point is crossed 4.4% (22.8%) of the 1000 runs over the whole time horizon considered. In the additive case and for $J=10\%$ ($J=1\%$), it is 7.4% (26.9%).

774 Appendix E. Sensitivities

775 Appendix E.1. Upper temperature threshold

776 The ratio of the SCC under risk-sensitive preferences to the SCC under
 777 additive preferences decreases with the upper threshold, i.e. a lower probability
 of tipping decreases the difference between the two criteria.

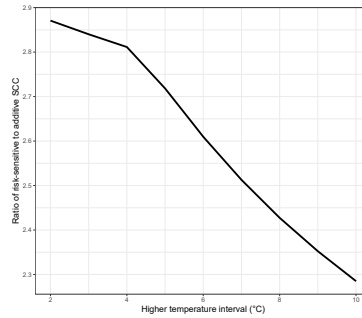


Figure E.9: Ratio of risk-sensitive to additive SCC for a benchmark $\epsilon = 0.133$, $J = 20\%$ and various upper temperature threshold.

778

779 Appendix E.2. Higher tipping damage J

We give the same graph as in the main text but for a larger range of J .

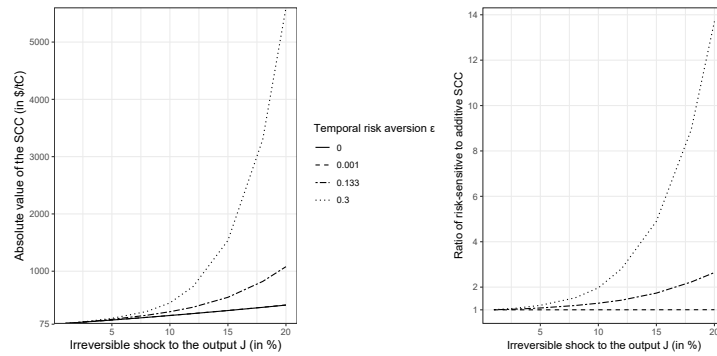


Figure E.10: Ratio of risk-sensitive to additive SCC at initial time for a benchmark $\epsilon = 0.133$ and various J .

780

781 *Appendix E.3. Inequality aversion*

782 We plot the log ratio of the SCC under risk-sensitive preferences to the SCC
 783 under additive preferences for different J and η , with $\epsilon = 0.133$. The ratio
 increases with the elasticity of marginal utility.

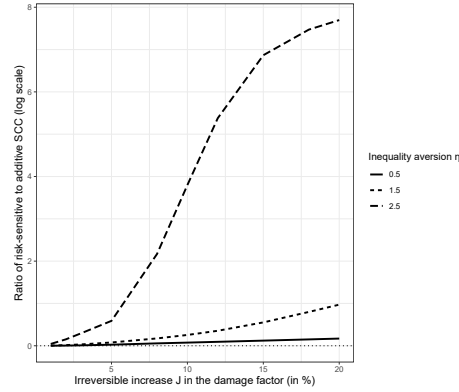


Figure E.11: Ratio of the SCC at initial time under risk-sensitive preferences on the SCC under additive preferences (benchmark calibration) for different J and η .

784

785 *Appendix E.4. Sensitivity - immediate decomposition*

786 We give the numerical decomposition for the immediate channels under risk-
 787 sensitive preferences for various J and ϵ .

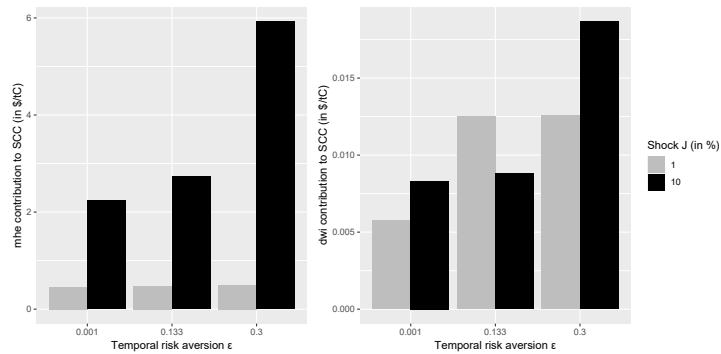


Figure E.12: Marginal contribution to the SCC at initial time (in \$) of the immediate *mhe* (left) and the immediate *dwi* (right) under risk-sensitive preferences for various J and ϵ . Results based on 1000 stochastic runs.

788 **Disclosure statement**

789 No competing interest to declare.

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Climate Policy under Fear of Model Misspecification

Jacopo Ghirri^{1,2,3*}, Massimo Marinacci⁴ and Massimo Tavoni^{1,2,3}

¹*Politecnico di Milano, Piazza Leonardo da Vinci 32, Milan, 20133, Italy.

²CMCC Foundation - Euro-Mediterranean Center on Climate Change,
Via Marco Biagi 5, Lecce, 73100, Italy.

³RFF-CMCC European Institute on Economics and the Environment,
Via Bergognone 34, Milan, 20144, Italy.

⁴Università Bocconi - Department of Decision Sciences, Via Roentgen 1,
Milan, 20136, Italy.

*Corresponding author(s). E-mail(s): jacopo.ghirri@polimi.it;

Abstract

Models -including those used in climate change analysis- are rough approximations of reality, and thus 'all wrong'; yet, the implications of model misspecification for climate decision-making have yet to be quantified. Here, we use recent advances in decision theory to assess how fear of model misspecification influences salient climate policy choices, such as the stringency and overshoot of the carbon budget. We apply the decision framework to emulators of IPCC scenarios, quantifying mitigation costs and economic damages from climate change. Our findings indicate that when decision-makers consider that established models may be systematically inaccurate, they adopt more stringent climate policies with lower carbon budgets and reduced reliance on emissions overshoot. These results highlight the importance of integrating deep uncertainty into climate decision-making, reinforcing the case for precautionary and robust policy choices in the face of unknown risks.

1 Introduction

While the case for climate action is clear and scientifically established, many uncertainties remain regarding how, when and by which strategy we should mitigate GHG emissions and adapt to increasing risks. This is a consequence of multiple, profound

sources of uncertainty arising from the long-lasting nature of climate change and the uncertainty of both physical and human components. Process and statistical modelling are central tools for informing policy actions with long-lasting consequences. Yet, their forecasts and projections are heavily influenced by various factors, many of which are ambiguous. The extent to which climate change will affect economic development is exemplary. Traditionally, climate damages were considered small relative to the projected economic progress, thus implying moderate mitigation [1]. Though this view still partly holds [2, 3], another body of literature has found significantly higher economic and inequality repercussions from climate change [4–6]. This example confirms the pivotal role of model uncertainty in climate economic modeling: we have no way of knowing which is the right one.

What’s more, none of the existing models might be right: models are highly simplified abstractions of realities, and as such wrong by design: what should we do in the interest of the world? One possibility is to abandon modeling altogether, but given the need of quantification and their relevance to society this might not help solve high stake policy issues [7, 8]. Another is to take model misspecification seriously and embed it into policy support assessments. Here, we do so by applying newly developed decision theory frameworks [9] to the case of climate change. The main objective is to assess how model misspecification affects climate policy, both in terms of ambition and in its design, especially regarding climate overshoot.

The centrality of uncertainty and risk management in climate change mitigation is well-established and has been the focus of research for decades [10]. Following this logic, decision makers should not rely solely on point estimates or expected outcomes. Instead, they need to understand the probability distribution of the key decision variables and adopt robust decision-making procedures [11]. This has only partly materialized in relevant assessments such as those of the IPCC, where parametric, within-model uncertainties are often overloooed in favour of model ensembles used to capture cross-model variations [12].

Every model is, however, conditional on its assumption [13]. Each model reflects the choices made by its developers, and different approaches, assumptions, and theories lead to different probability distributions of outcomes. This diversity in risk quantification challenges decision makers, who must navigate the ambiguity caused by varying or conflicting information. This is the framework of model uncertainty [14]. Decision making under model uncertainty matters for the climate policy design, and the criteria adopted for navigating ambiguity play a significant role in the policy selection process [15]. While it is understood that the delineation of targets, strategies, and policies must account for and integrate the uncertainty within and between models [14, 16], none of the existing numerical assessments has considered the possibility that the right model is outside the set of established ones.

Models are, by their nature, simplifications, and the impact of their approximations and inaccuracies is itself uncertain [9]. A decision maker might be concerned that a model’s simplification or inaccuracies could lead to overestimating the benefits of a policy or underestimating its costs. This could prompt them to adopt a more conservative approach that reflects a risk-averse stance. This paper quantifies the impacts of model misspecification on climate policy, capturing uncertainties beyond those within

and across models. We leverage the most recent developments in decision theory under uncertainty and quantify how the fear of model misspecification affects the stringency and design of climate mitigation pathways -defined by the global cumulative emissions till 2100 and their overshoot. We calibrate the model to the IPCC AR6 scenarios and models for mitigation pathways costs, to published damage functions for impacts, and for IPCC AR6 for climate uncertainties. Within this framework, we employ decision-making criteria that reflect neutrality toward ambiguity, aversion to model uncertainty, and different levels of fear of model misspecification. We then compare the impact that these attitudes have on policy choices.

Our findings suggest that in response to concerns about model misspecification, decision makers should opt for more ambitious climate targets and allow less room for emission overshoot.

2 Fearing Misspecification

At the core of the framework developed in [9] is the definition of a space of models, Δ . For this analysis, we call models the association of probability distributions on a utility to each action taken by the decision maker. Models, therefore, inform the decision maker about the expected utility and the associated risks of climate targets.

Within Δ , we distinguish between two broad categories of models: *structured* and *unstructured* models. Structured models (SMs), which define a subspace $Q \subset \Delta$, are those grounded in rigorous scientific understanding. They are derived from established theories, with computable and verifiable assumptions. Broadly speaking, any model used in the peer-reviewed scientific literature qualifies as a Structured model. In practice, established models are the ones with stronger track records in science and bigger community of practice: in the case of climate, these could be the models reviewed in the IPCC. Unstructured models, on the other hand, provide probability distributions over the outcome of climate targets without substantive motivation. They represent alternative models that may be unavailable to us due to being uncomputable, based on speculative approaches, lacking clear justification, or simply being incorrect. While inherently unreliable and potentially arbitrary, they do serve as a statistical artifact to formally assess the limitations of structured models, helping to explore the potential impact of simplifications, approximations, and errors.

Although there is an intrinsic value in structured models, there is no assurance that the ground truth is being precisely captured by any of them, nor that it lies in the confines of Q . It is indeed possible that an unstructured model is a better representation of the real-world mechanism.

Accounting for such risks, translates into expanding the framework of model uncertainty. While criteria like MaxMin Expected Utility [17] represent full aversion to model uncertainty by evaluating the utility of any decision-maker action as the worst expected utility indicated by structured models, the criteria in [9] expands this to the space of unstructured models too, as summarized in Formula 1.

$$V(f) = \min_{m \in \Delta} \left\{ \int u(f) dm + \lambda \min_{s \in Q} KL(m||s) \right\} \quad (1)$$

Where f is the policy decision, $V(f)$ is its evaluation, $u(f)$ is the utility under the respective model-induced probability distribution. KL is the Kullback–Leibler statistical distance measure, and λ is a tunable parameter. The lower the λ , the lower is the penalty added to Unstructured Models for being discordant with respect to Q , hence the higher is the fear of model misspecification.

The penalty term added to unstructured models serves two purposes. First of all, even within the context of model misspecification, structured models are considered more reliable than unstructured ones, which hence suffer larger penalties the more their conclusions differ from those informed by scientific understanding. Secondly, there is a problem of computability. The problem with no penalty, equivalent to $\lambda = 0$, complete mistrust of structured models, is equivalent to applying the MaxMin Expected Utility criterion across the entire model space. However, being unstructured models unavailable and uncomputable, the problem has no solution. The penalty term allows to compute Formula 1 under the assumptions detailed in [9]. In the context of this framework there are two core assumptions that allow computability. The first consists in extending the notion of structured models to encompass also any convex combination of structured models. This implies considering model ensembles as structured models themselves, which is consistent with how ensembles are used in literature [12]. The second assumption requires absolute continuity of Δ with respect to Q , meaning that the effective domain of probability distributions in Δ cannot be larger than that explored by probability distributions in Q . If all structured models agree to assign zero probability to a range of outcomes, then so will unstructured models. In other words, unstructured models can adjust the probability assessments made by structured models, such as by increasing the likelihood of worse outcomes for certain targets. However, they remain constrained by the boundaries set by structured models. If all structured models agree that a particular outcome is impossible, no unstructured model can assign it a nonzero probability.

Under these assumptions, Formula 1 can be simplified into its computable form, reported in Formula 2.

$$V(f) = \min_{s \in Q} -\lambda \log \int \exp \left(-\frac{u(f)}{\lambda} \right) ds \quad (2)$$

Furthermore, since we have a finite collection of core structured models and thanks to the monotonicity of the functions involved, the problem can be further simplified as in Formula 3, avoiding the explicit computation of convex combinations of models.

$$V(f) = \min_{s \in SM} -\lambda \log \int \exp \left(-\frac{u(f)}{\lambda} \right) ds \quad (3)$$

3 Quantifying model misspecification

Figure 1 illustrates the entire procedure.

We identify climate policies as the combination of a carbon budget and the extent to which it can be temporarily exceeded. These are two focal points in climate policy. We take 2100 as end-point by which the carbon budget must be met, with or without temporary overshoot. The carbon budget defines the long-term stringency of policy

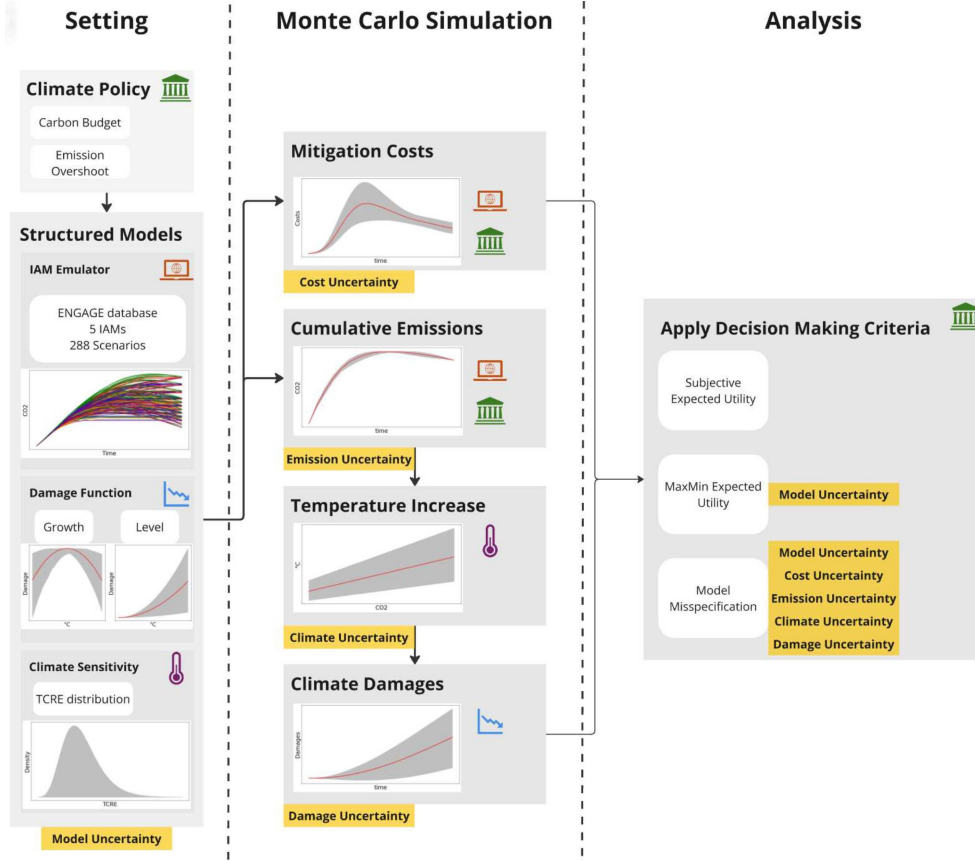


Fig. 1 A climate policy is evaluated by each structured model by producing Monte Carlo samples of its associated mitigation costs and damages. Different Decision Making Criteria are responsive to different sources of uncertainty, introduced at each step of the procedure. We report through the different icons at which step the different elements of the setting play a role.

measured by temperature increase in 2100, whereas the emission overshoot determines its temporal evolution. The interplay between these two focal policy points had been overlooked by scenario designs that freely allowed climate overshoot [18, 19]. It has been systematically explored only recently in a model comparison project that served as the backbone of IPCC AR6 scenarios. We exploit this database to derive emission pathways and mitigation costs. We train 5 couples of emulators, each linking climate policies to either mitigation costs, as a percentage of GDP, from 2010 to 2100, or to cumulative emissions of CO_2 , from 2010 to 2100. Each couple of emulators is trained using scenarios from a different integrated assessment model (IAM). To obtain robust emulators from a limited dataset, we employ Functional on Scalar Regression [20]. See Methods for additional details. To derive the temperature change associated with each

emissions pathway, we use the linear relationship detailed in [21], allowing the Transient Climate Response to Cumulative CO_2 Emissions parameter to vary according to its distribution, using the IPCC AR6 estimates.

Lastly, we quantify the economic impacts of climate change according to the two main paradigms currently discussed in the literature. A first approach, referred to as a *level* approach, attributes a direct link between temperature above pre-industrial level and a loss in percentage of GDP. We apply this approach by using the preferred damage specification in the meta-analysis of [22], using the confidence interval of the regression coefficients to quantify damage uncertainty. The second approach, referred to as *growth* approach, applies damages to the GDP growth rate. In particular, we use the short run specification in [4]. To quantify uncertainty around the damage function parameters, we use the coefficients from 1000 bootstrap regressions of the same specifications using the replication code from [23]. By considering these two climate impact frameworks and their respective uncertainties, we directly account for the profound and evolving uncertainty that characterizes this field of research.

Both costs and damages of climate actions are applied upon a middle-of-the-road scenario of economic development (SSP2) [24]. We compute a Net Present Value between 2020 and 2100 at a 3% discount rate, as it is the one where the trade-off between costs and damages is most evident. Sensitivity over the choice of this parameter is reported in Figure 5 of the Supplementary Information.

We explore a grid of climate policies, with carbon budgets ranging from 750 to 2000 $Gt CO_2$, and carbon budget overshoots from 0 to 200 $Gt CO_2$. We define these ranges as they allow to cover the range of Paris Agreement's targets while remaining sufficiently within the ranges explored in the ENGAGE scenario database.

Finally we apply the model misspecification criteria to identify robust policy choices, in terms of carbon budget and allowed overshoot of said budget. We explore how the target selection procedure is affected by different decision criteria, reflecting different stances in face of uncertainty.

As shown in Figure 2, two main policy trade off emerge. The first one involves finding a carbon budget balancing costs and damages. Increasing the carbon budget, there is a general decrease in costs of mitigation. This decrease is however strictly dependent on the IAM emulator, testifying significant model uncertainty in the costs of reducing emissions, and generally nonlinear. At the same time, looser targets correspond to higher climate damages, and while this increase is almost linear for level based damages, it is not for growth based ones. The second tradeoff is a temporal one, as overshooting carbon budgets allows for postponement of action, shifting costs toward the end of the century, both in terms of higher mitigation costs arising from the greater emission reduction effort in later decades as well as higher climate damages[25]. The extent to which climate economic damages increase with the overshoot is driven by the typology of damage function, with significant impacts only for the growth based damage, which assumes long-lasting persistence of climate shocks on the economy.

Furthermore, Figure 2 shows how the different dimensions of the problem induce different levels and types of uncertainty. Within each modeling framework, there is relatively little uncertainty in the relationship between mitigation costs and carbon budget, but significant variations across different IAMs (in the light of their different

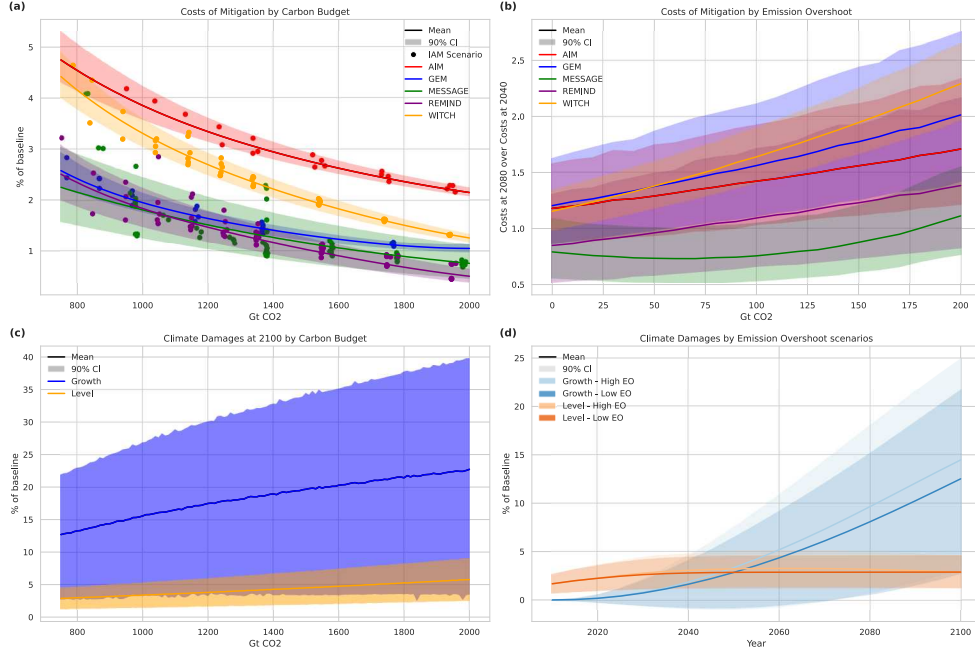


Fig. 2 (a) Relation between carbon budget and costs of mitigation. We report the NPV of mitigation costs (from 2020 to 2100, expressed as percentage of baseline GDP and discounted at 3% per year), for a set of models participating in the model comparison with sufficient data coverage. (b) Relation between carbon budget overshoot and the time distribution of costs of mitigation, defined as the ratio of mitigation costs in 2080 over 2040. (c) Impact of carbon budget on climate economic damages. We report the damages sustained in 2100 as a percentage of baseline GDP. (d) Impact of carbon budget overshoot on climate damages. For a total carbon budget of 750 GtCO₂, we compare a high overshoot and a no overshoot scenarios (200 and 0 GtCO₂ of budget overshoot respectively). We hence compare the highest and lowest amount of explored emission overshoot for the lowest carbon budget in the analysis.

characteristics). For climate impacts, while model uncertainty remains significant, there is a also a very significant uncertainty within each model.

Moreover, although overshooting emission targets does lead to discernible effects, namely the postponement of climate action and the resulting delay in associated costs, and increasing expected climate damages, the signals are difficult to isolate due to the high levels of uncertainty in both the cost and damage dimensions. This underscores the complexity and risk of pursuing overshoot pathways, and highlights the need for a more thorough exploration of their implications in policy analysis.

4 Results

As shown in Section 3, our emulators effectively capture the established relationships and trade-offs between emission targets and expected outcomes, along with uncertainty ranges consistent with those observed in the climate economics literature, both within

and across available -i.e. structured- models. We now apply different decision making criteria and explore the consequences of fear of model misspecification.

The traditional approach is Subjective Expected Utility (SEU) with equal weighting [26], a criterion indifferent to uncertainties, defining the value of a policy by the mean expected value across structured models. We also consider MaxMin Expected Utility (MaxMinEU) [17], a framework weary of model uncertainty, as it defines the value of a policy as the lowest expected value across structured models. We compare these two previously explored frameworks -neither of which included for the fact that none of the available models could be right- with the model misspecification one [9] for different levels of fear of model misspecification. The tuning of the λ parameter in Formula 3 is a delicate task, as sensible values are dependent on the different utility distributions and remain challenging to interpret. To address this, we explore a wide range of λ values, framing the impact of decision-making criteria as a continuum of increasing levels of fear of model misspecification. Rather than assigning explicit thresholds for what constitutes "high" or "low" fear, we present a comparative analysis, allowing the relative influence of model misspecification concerns to emerge without imposing a rigid interpretation.

Figure 3 shows our main results. First of all, a well-known trade off between climate policy stringency and temporary overshoot is depicted: very stringent carbon budgets compatible with low warming cannot be met without a temporary exceedance. However, for a given carbon budget the extent of overshoot is significantly affected by the choice of decision criteria. For example, a Paris-compliant budget of an 800 GtCO₂ budget can have an overshoot range of almost 100 GtCO₂ (from 50 to 140 GtCO₂) depending on how uncertainty is accounted for. Previous studies have shown that negative emissions and overshoot carry significant risks in terms of environmental, social and economic sustainability [27–30]. Here, we show that the way uncertainties are represented have a similar bearing on the extent of overshoot.

Comparing decision making criteria, MaxMin Expected Utility, being weary of model uncertainty, guides the decision maker toward less stringent targets than Subjective Expected Utility. This outcome is driven by the presence of scenarios, particularly those from the AIM model, that predict significantly higher emission reduction costs, as shown in Figure 2. A decision maker averse to model uncertainty is therefore less likely to underestimate the potential costs of ambitious targets. Sensitivity to the exclusion of this model is discussed in the Supplementary Information.

Regarding model misspecification, the new criterion introduced in this paper, we find that when decision makers fear that none of available models is the right one, more stringent and precautionary climate policies are warranted, both in terms of carbon budget and the amount of emission overshoot associated with it. This is due to the rapidly increasing level of uncertainty associated with climate damages, as is shown in Figure 2. As the fear of model misspecification intensifies, more stringent carbon budgets are selected. While this leads to higher emission overshoots, we emphasize that for any given carbon budget, the extent of overshoot decreases as concern over model misspecification grows.

Stricter emissions targets are directly tied to limiting temperature increases, but they also require increasingly ambitious Net Zero timelines [31]. We find that with

high fear of model misspecification, CO2 emissions go to zero as early as possible (i.e. 2050, see Panel b of Figure 3).

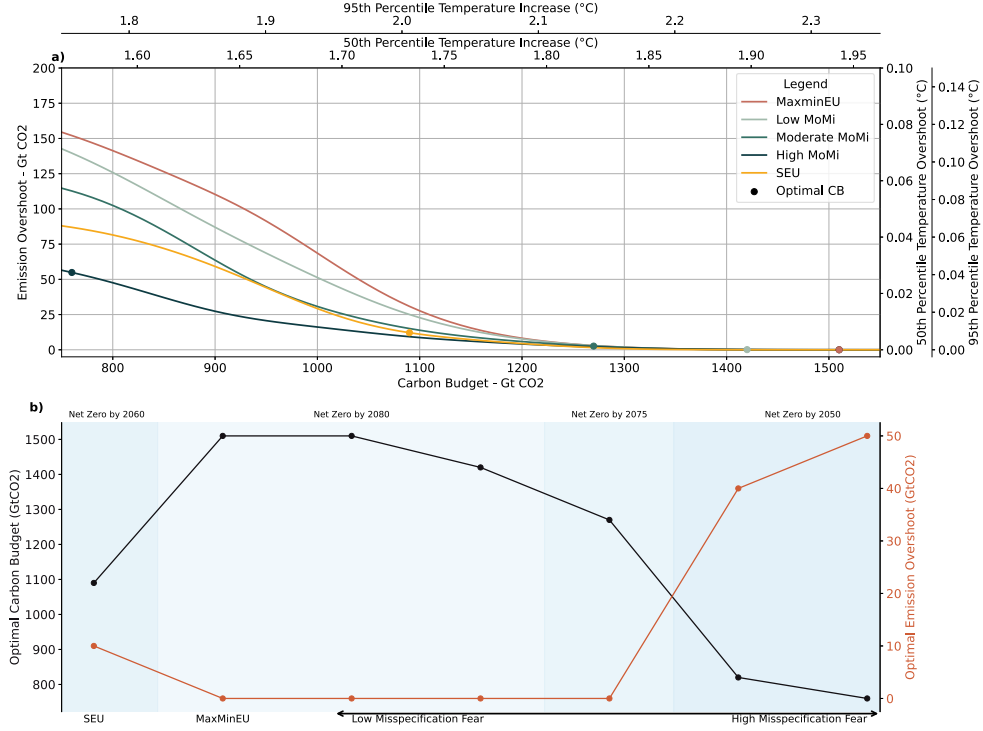


Fig. 3 (a) Climate policy space in terms of carbon budget level and overshoot, for the different decision making criteria. (b) Optimal climate policy selected by Subjective Expected Utility (SEU), MaxMin Expected Utility (MaxMinEU), and increasing levels of fear of Model Misspecification (MoMi).

We analyze the impact of each source of uncertainty by systematically replacing one source at a time with its central estimate while keeping the others unchanged. The results of this procedure are presented in Figure 4. It is worth noticing that the strategy profiles derived from Subjective Expected Utility and MaxMin Expected Utility remain fundamentally unchanged across these scenarios. Since these approaches do not account for uncertainties within each structured model, any observed variations are minimal, and primarily due to the inherent variability of the simulation environment. In contrast, under concerns of model misspecification the different sources of uncertainty lead to heterogeneous policy responses. Discarding climate uncertainty has minimal impact on the assessment. Similarly, the uncertainty on cumulative emission and mitigation costs pathways, introduced by IAM emulators, plays a secondary role, with its exclusion leading to only marginal changes in policy recommendations. When excluding either uncertainty type, the policy provision remains similar: for high fear

281 of misspecification, choose a very stringent carbon budget and the lowest possible over-
 282 shoot compatible with that level of policy ambition. In contrast, uncertainty in climate
 283 damages plays a crucial role. Ignoring this source of uncertainty significantly reduces
 284 the relevance of concerns about model misspecification, as damage function calibration
 285 is a particularly challenging and delicate task [32]. When ignoring climate damage
 286 uncertainty, the decision maker chooses a laxer climate policy.

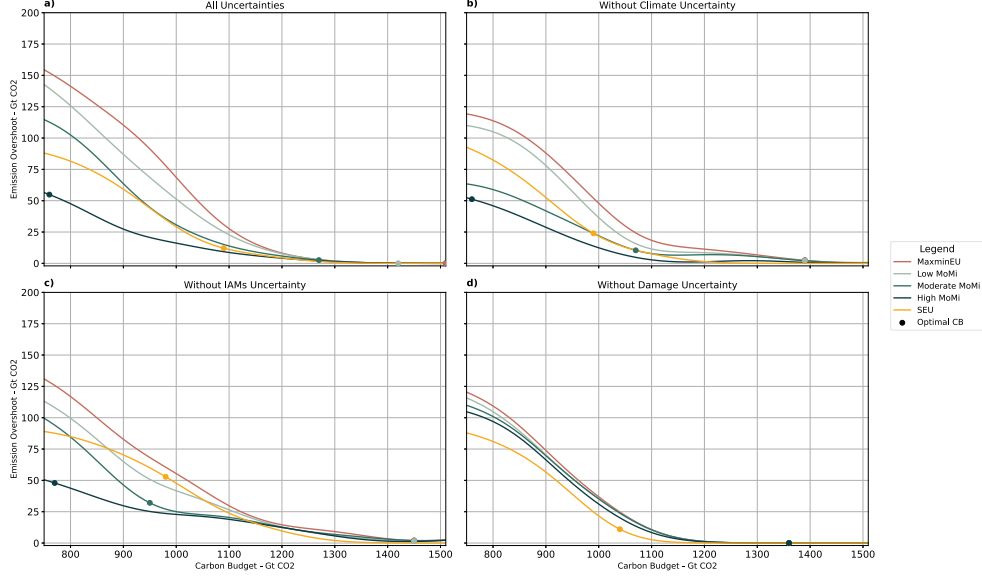


Fig. 4 Impact of freezing one uncertainty source at the time on policy recommendations, for the different decision making criteria. (a) Baseline setting, incorporating all sources of uncertainty. (b) Climate uncertainty removed by fixing the transient climate response to cumulative carbon emissions (TCRE) to its median value of 1.8 K EgC^{-1} , as reported in [21]. (c) IAM emulator uncertainty removed by using central estimates of mitigation costs and emissions pathways, without accounting for residual variance. (d) Damage function uncertainty removed by fixing damage parameters to best estimates from [4, 22].

287 This result holds when replicating the analysis at different discount rates and when
 288 excluding the high mitigation cost model, AIM, from the set of structured models.
 289 The results of these robustness tests are provided in the Supplementary Information.

290 5 Conclusions

291 We have shown that fear of model misspecification [9] systematically shifts climate
 292 policy toward more stringent and precautionary strategies. When policymakers recog-
 293 nize that existing models may be fundamentally incomplete, they favor lower carbon
 294 budgets and reduced emission overshoots, adopting a precautionary stance to hedge
 295 against uncertain climate damages.

A proper treatment of uncertainty is recognized as fundamental for robust policy design, as well for communication to the larger public and to experts and policy makers [33–38]. For example, in the 5th assessment report, the IPCC has issued specific recommendations on how to improve its treatment through codified likelihood and confidence statements [39]. These heuristics have helped standardize the treatment of uncertainty, but have failed to connect to and be informed from rigorous, axiomatic approaches developed by decision theorists [40].

The recent theory distinguishes three types of uncertainty: risk, ambiguity and misspecification [41]. Previous assessments have focused on the first two, namely on variations within and across existing models [10–12, 14–16]. This paper extends this perspective by considering for the first time the possibility that any current model does not fully capture the true dynamics of the climate-economy systems. This distinction is critical, as it challenges the assumption that model diversity alone is sufficient to account for uncertainty. By incorporating a formal mathematical framework that accounts for varying degrees of model misspecification fear, we provide a systematic approach to understanding how decision-makers adjust policy in response to these concerns.

Determining the appropriate level of model misspecification fear is inherently challenging, and translating it into a formal decision parameter introduces additional complexities. However, it remains essential given the deep uncertainties shaping climate policy, uncertainties that extend beyond those explored in this analysis. The transformation of energy systems [42], the deployment of emerging technologies such as carbon capture [43] and solar radiation management [44], all introduce potential biases and risks of underestimating key impacts.

At the same time, recognizing model limitations does not justify neglecting uncertainty quantification. Instead, our approach highlights the need for deeper model development, scenario analysis, and uncertainty exploration. Model misspecification is meaningful only when based on a well-explored range of climate-economic outcomes. Without rigorous uncertainty assessment, decision criteria risk providing incomplete coverage, potentially leading to misdirected policies.

Given these uncertainties, integrating model misspecification considerations into decision-making is not just a theoretical exercise. It points to the need to develop a sufficiently broad and inclusive set of ‘structured’ models and scenarios to span a sufficiently large realm of possibilities. A scientifically validated, plurality of approaches can help better explore the possibilities of model misspecification and help define precautionary, robust climate strategies.

6 Methods

6.1 Sources of Uncertainty

Not all uncertainties are created equal; they can be understood as forming a two-level hierarchical structure. The first level encompasses uncertainties affecting models. These uncertainties can arise from imperfect knowledge of parameters, or inherent natural variability, and can be described as within models themselves. The second,

deeper level involves uncertainties between models, where it is not specific parameters that vary, but the model structures themselves and the prior assumptions they encode. Each model implicitly reflects a particular set of beliefs about the plausibility of different mechanisms or contingencies.

These hierarchical uncertainties renders the decision making task more difficult, as they do not just represent variability over an outcome, but disagreements and ambiguity on how to compute it and its underlying mechanisms. This makes accounting for model misspecification essential, as it addresses not only parametric uncertainties affecting models, but also the deeper uncertainty surrounding the models themselves. These layered uncertainties are present throughout the entire evaluation procedure.

The costs associated with meeting a given climate target depend not only on parameter uncertainty within individual IAMs, captured by our emulators, but also on deeper differences in the models' embedded assumptions about, for instance, speed of technological development, or targets' impacts on power demand, justifying their different central estimates.

In particular, we employ scenarios from five IAMs, reflecting distinct structural choices and focuses. AIM is a general equilibrium model with technology explicit representations of energy and land use sectors. GEM focuses on market instruments for environmental policy within a computable general equilibrium framework. MESSAGE combines partial equilibrium models for energy and land use, soft-linked to a macroeconomic model. REMIND couples a global economic growth model with a detailed energy system model, allowing for a high detail in technology options. WITCH embeds in a game-theory framework an economic optimal growth model with a bottom up energy sector, and a simple climate model, capturing optimal regional responses to climate change, and considering externalities in technological change.

Moreover, even though targets are fixed, models show variability in their implied emissions pathways, reflecting their prior beliefs on feasible paces of decarbonization. Translating these pathways into temperature increases introduces physical uncertainty, through the distribution of climate sensitivity, which remains an irreducible source of variability. Finally, the translation of temperature into economic damages involves both parametric uncertainty, as in the calibration of damage functions, and structural disagreement over their form, with level-based and growth-based approaches reflecting fundamentally different beliefs about the persistence of climate impacts. Together, these uncertainties illustrate that ambiguity lies not only in the outcomes we forecast, but in the very models we use to generate them.

6.2 Scenario Selection

The ENGAGE database¹ provides an ample collection of scenarios, coming from a multitude of Integrated Assessment Models. This was the model comparison project which provided most scenarios to the latest assessment of the IPCC, and also the only one to systematically explore the role of overshoot. We selected this important study for these two reasons.

We select scenarios according to the satisfaction of all the following criteria:

¹<https://iiasa.ac.at/models-tools-data/engage-scenario-explorer>

- GDP is reported in Market Exchange Rates for all decade values between 2020 and 2100.
- CO_2 emissions are reported for all decade values between 2010 and 2100.
- Carbon budget is lower or equal to 2000 GtCO₂.
- Scenario's policy dimension is either National Policies implemented (NPi) or National Determined Contributions implemented (NDCi).
- The IAM has a scenario 'EN_NPi2100', with only current policy implemented.

This selection identifies 288 IAM scenarios, grouped according to Table 1.

Table 1 Number of selected scenarios, grouped by the respective IAM.

IAM	AIM	GEM	MESSAGE	REMIND	WITCH
N. of Scenarios	28	33	99	78	50

For each scenario we extract CO_2 emissions pathways, translated into Cumulative Emissions, and GDP projections, defining mitigation costs as the percentage GDP loss of each scenario with respect to the respective baseline.

6.3 IAM emulators

Due to the restricted number of scenarios accessible for each Structured Model and the necessity for interpolation and extrapolation across an extensive range of targets, we need to use a method that offers flexibility, robustness, and efficiency with minimal data. Hence, the primary modeling technique employed in this study is Function-on-Scalar Regression [20, 45].

In the context of this work, the response of a Functional on Scalar Regression model is a function of time, as we model pathways for cumulative emissions and mitigation costs. The basic formulation is reported in Formula 4, with $y_i(t)$ for $i = 1, \dots, N$ being a set of N functional responses, z_{ij} being the j -th out of M scalar covariates for observation i , and $\epsilon_i(t)$ being the corresponding functional error term.

$$y_i(t) = \alpha(t) + \sum_{j=1}^M z_{ij} \beta_j(t) + \epsilon_i(t) \quad \forall i = 1, \dots, N \quad (4)$$

The functional terms $\beta_j(t)$ are estimated as linear combinations of basis functions. Defining q the dimensionality of the embedding space for scenario data, Formula 4 can be rewritten as Formula 5.

$$\sum_{k=1}^q y_i^k \theta_k(t) = \sum_{k=1}^q a_k \theta_k(t) + \sum_{j=1}^M z_{ij} \sum_{k=1}^q b_{jk} \theta_k(t) + \sum_{k=1}^q \epsilon_{ik} \theta_k(t) \quad \forall i = 1, \dots, N \quad (5)$$

With $\theta_k(t)$ for $k = 1, \dots, q$ being the chosen set of basis functions.

To estimate these coefficients, we employ the Penalized OLS implementation provided by [20], as it allows to perform this task under a generalized Ridge penalization framework, and is found to be less vulnerable to undercoverage in small samples [20].

Two Functional on Scalar Regression models are trained for each structured model, one for modeling mitigation costs and one for modeling cumulative emission pathways.

Each regression model uses carbon budget and emission overshoot as predictors, with the possibility of nonlinear and interaction terms. The formula of each regression is selected via Leave-One-Out Cross-Validation, minimizing the Mean Squared Error of the forecasted pathway.

We embed scenario data in a functional space with a basis of 30 splines of 4-th order, ensuring a smooth functional mapping while avoiding excessive variability on the second derivatives. This smoothing effect is accounted for in the cross-validation performance metrics, and we find models to be robust across different specifications, given the high flexibility allowed by the functional approach.

Sampling new pathways follows a two-step procedure. Initially, we derive the expected pathway from the Functional on Scalar Regression model linked to the specific structured model under consideration. Subsequently, to address the uncertainty surrounding expected pathways, we add a random realization from a Gaussian Process distribution. This Gaussian Process distribution is fitted atop the regression residuals generated during the training phase of the respective regression model. Given heterogeneous uncertainty across the time horizon, we do not assume stationarity of the Gaussian Process, exploiting the fact that we do not need to perform neither extrapolation nor interpolation between timesteps.

The second step, consist in post-processing the sampled random pathway, in order to enforce consistency with the climate policy in the case of cumulative emissions, and heterogeneous uncertainty with respect to targets in the case of mitigation costs.

Model selection for each Functional on Scalar Regression model is performed by Leave-One-Out Cross-Validation monitoring the Root Mean Square Errors.

6.4 Computing Climate Damages

A linear relationship between cumulative CO_2 emissions and temperature increase is outlined in [21], which identifies the Transient Climate Response to Cumulative CO_2 Emissions (TCRE) parameter to follow a log-normal distribution. Hence, we obtain temperature increase pathways from each emission scenario, with the TCRE parameter being independently sampled from the appropriate log-normal distribution [21].

The economic quantification of the effects of climate change is a delicate task. There is not yet a definitive theoretical or empirical consensus on how to account for them, and new sets of damage functions are continuously proposed [6, 22, 46, 47]. The main element of discussion in this literature is the extent of persistency of climate shocks on the economy over time. Here, we employ the two leading paradigms, which posit that climate damages are either transient ('level based' approach) or infinitely persistent ('growth based' approach). Reality might be in the middle, with long-lasting but temporary impacts [6, 48].

To represent level based damages, we follow [22], where an increase in global mean temperature is directly linked to a proportional loss of global GDP according to a

quadratic function. We use the preferred damage specification, using the confidence interval of the regression coefficients to quantify damage uncertainty.

To quantify growth based damages, we employ the approach in [4], where temperature changes have an impact on the growth rate of each country’s GDP per capita. Parameter uncertainty within the damage function is addressed using the coefficients from 1000 bootstrap regressions of the same specifications using the replication code from [23].

Since in level-based damages the link is expressed directly between temperature and percentage loss of GDP, one just needs to sample the parameters for the quadratic expression. For growth-damages, we instead follow the procedure detailed in the replication code from [49], as one needs to downscale temperatures at the national level, and applying damages to GDP per capita growth rate. We employ the SSP2 [24] baseline projections for both GDP and population, computing climate damages as the percentage loss in GDP with respect to the baseline GDP projection.

6.5 Utility

Mitigation costs and climate damages, being both expressed in terms of portions of global GDP loss, can be applied to the baseline SSP2 GDP projection. A metric of economic output net of costs and damages is hence obtained, to be interpreted as a Net Global GDP. We compute a Net Present Value (NPV) from 2020 to 2100 of this metric, at a 3% discount rate. This way, the decision maker has for every climate policy, 10 distributions of NPVs, one for each structured model. Decision making criteria are applied using these distributions, approximated empirically via Monte Carlo.

6.6 Decision Making Criteria

We select the optimal levels of Carbon Budget and Emission Overshoot using three distinct decision making criteria. Decision making criteria embed in mathematical formulae different preferences of a decision maker, and in particular different attitudes toward risks and uncertainties.

Subjective Expected Utility with equal weighting [26], reported in Formula 6, attributes value V to policy f as the average expected utility across all structured models SM . This approach averages out both within-model uncertainties and differences between models, effectively representing a decision maker who is completely indifferent to uncertainty and unaffected by risk aversion.

$$V(f) = \frac{1}{\text{card}(SM)} \sum_{s \in SM} \int u(f) ds \quad (6)$$

MaxMin Expected Utility [17], reported in Formula 7, evaluates a policy based on the lowest expected utility across structured models. reflects a decision maker who is averse to model uncertainty. When faced with multiple and potentially conflicting estimates of an outcome, they choose actions that guard against the worst-case scenario, not knowing which model is the most accurate in given instance. However, this criterion still assumes fundamental trust in the models: once the most pessimistic model is identified, the policy is evaluated based on its central estimate.

$$V(f) = \min_{s \in SM} \int u(f) ds \quad (7)$$

489 Model Misspecification [9], shown in Formula 1 and discussed in detail in Section
 490 2, evaluates a policy by extending the MaxMin approach to include not only struc-
 491 tured models but also unstructured ones. A penalty is applied to unstructured models,
 492 increasing with the degree of deviation from the structured models. This reflects a
 493 decision maker who is not only concerned with model uncertainty, but also with the
 494 possibility that all structured models may be fundamentally misspecified, demonstrat-
 495 ing a deep mistrust in the reliability of model based projections due to their inherent
 496 inaccuracies and simplifications.

Declarations

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