Optimal climate policy under socio-economic uncertainty

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Zusammenfassung

Diese Dissertation untersucht Wege zur Minderung des Klimawandels und stellt neue Ansätze zum Umgang mit sozioökonomischer Unsicherheit bei der szenariobasierten Gestaltung der Klimapolitik vor. Angesichts der Komplexität des Klimawandels muss die Wissenschaft, die das Problem analysiert, interdisziplinär sein. Auch die Stochastizität und Unsicherheit, die alle Aspekte des Lebens auf dem Planeten umgeben, müssen in Studien, die das Problem untersuchen, berücksichtigt werden. Die Kombination gut etablierter Methoden der Unsicherheitsanalyse mit sozio-ökonomischen Szenarien ermöglicht neue methodische Ansätze zur Analyse von Klimaschutzpfaden. Sozio-ökonomische Unsicherheit bezieht sich auf unterschiedliche zukünftige Pfade des globalen Bevölkerungswachstums, der Wirtschaftsleistung und der Entwicklung gesellschaftlich relevanter techno-ökonomischer Parameter. Wie wichtig ist der Einfluss der Unsicherheit des Wirtschaftswachstums auf zukünftige Emissionen und Klimaziele? Wir berücksichtigen die Unsicherheit explizit mit der stochastischen Version eines Energie-Wirtschafts-Klima-Modells. Emissionsintensitätsziele werden als ein Mittel zur Absicherung gegen Wachstumsunsicherheiten gesehen, aber unsere Studie zeigt durch einen Multikriterienvergleich von absoluten Emissionszielen und Emissionsintensitätszielen, dass absolute Ziele mehr Vorteile haben. Darüber hinaus werden weltweit schnelle Veränderungen der wirtschaftlichen Kosten von Energietechnologien beobachtet. Es ist schwierig, solide Vorhersagen über die zukünftige Entwicklung und die Rolle dieser Technologien bei der Gestaltung der Energie- und Klimapolitik abzuleiten. Diese Doktorarbeit bietet eine Sensitivitätsanalyse der Auswirkung von Unsicherheiten in techno-ökonomischen Parametern der Energieerzeugung auf Klimaschutzpfade und hebt die wichtige Rolle des Transportsektors hervor. Schließlich gibt es verschiedene Schemata, die Gerechtigkeit des Klimaschutzes zu beschreiben, die ein oder mehrere Gerechtigkeitsprinzipien ansprechen und letztendlich beschreiben, wie die Last der Minderung des Klimawandels zwischen den Weltregionen verteilt wird. Wie interagiert die sozioökonomische Unsicherheit mit der Lastenverteilung des Klimaschutzes? Um diese Frage zu beantworten und eine Lücke in der Literatur zu füllen, bietet diese Doktorarbeit eine Analyse verschiedener Lastenverteilungsschemata über Regionen

hinweg und unter sozioökonomischer Unsicherheit und zeigt, dass eine Welt, die sich in Richtung Nachhaltigkeit orientiert, die Last der Klimastabilisierung leichter zwischen den Regionen verteilen wird.

Abstract

This doctoral thesis explores pathways towards mitigation of climate change and presents novel approaches to tackling socio-economic uncertainty in scenario-based climate policy design. Given the complexity of climate change, the science that analyzes the problem has to be inter-disciplinary, while the stochasticity and uncertainty surrounding all aspects of life on the planet needs to be considered in studies investigating it. Combining well established uncertainty analysis methods with socio-economic scenarios facilitates new methodological approaches for analyzing climate mitigation pathways. Socio-economic uncertainty refers to different future paths of global population growth, economic output, and development in techno-economic parameters relevant to society. How important is the effect of economic growth uncertainty on future emissions and climate targets? We explicitly account for uncertainty using a stochastic version of an en energy-economy-climate model. Emission intensity targets are considered means to hedge against growth uncertainty, but our study shows via a multi-criteria comparison of absolute versus intensity emission targets that absolute targets have more benefits. Further, rapid changes in economic costs of energy technologies are being observed globally. It is difficult to derive solid predictions on the future evolution and role of such technologies in shaping energy and climate policy. At the same time, different sectors of the economy feature different characteristics and decarbonization potentials. This thesis provides a sensitivity analysis of the effect of uncertainty in techno-economic parameters of energy generation on climate mitigation pathways and highlights the important role of the transport sector. Finally, several different schemes exist to describe the equity dimension of climate change mitigation, addressing one or more equity principles and ultimately describing how the burden of mitigating climate change is shared among world regions. How does socio-economic uncertainty interact with the burden sharing of climate mitigation? To answer this question and fill a gap in the literature, this thesis provides an analysis of several different burden sharing schemes across regions and under socio-economic uncertainty, and shows that a world leaning towards sustainability will distribute more easily the burden of climate stabilization between regions.

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Introduction

1.1 Motivation

Climate change is the most severe and complex environmental problem the world has faced to date. Further characteristics of climate change are its multi-faceted nature, the high uncertainty it entails, and its global scale. The scientific community informs the society in a) understanding the causes and state of the problem, b) assessing its natural, societal and monetary impacts, and c) exploring the alternative pathways leading to its solution. While the causes of climate change have been solidly identified as the anthropogenic intervention in Earth's natural cycles—which leads to changes in the way the atmosphere traps solar radiation—the exact magnitude of the problem and the approaches to its solution are under ongoing investigation and debate, due to its sheer complexity and because the continuous alarming signals reported by scientists are not taken into full consideration by governments. Further, several current extreme weather and natural phenomena are attributed to climate change by scientists but are not regarded as such by all politicians, whereas future impacts of climate change can not be fully understood due to the wide range of possible outcomes, spanning the natural, societal and economic sphere. Finally, pathways leading to sustainable solutions of the problem are subject to extensive debate, mostly due to the widespread understanding that many potential technological solutions are already present, but a successful implementation depends also on political will—and is consequently affected by the above discussions about the physical science and the impacts—and market as well as social dynamics. Given the complexity of the issue, the science that analyzes climate change has to be inter-disciplinary, while the stochasticity and uncertainty surrounding all aspects of life on the planet needs to be considered in studies investigating climate change.

This doctoral thesis explores item c) above—alternative pathways towards mitigation of climate change—and presents novel approaches to tackling socio-economic uncertainty in scenario-based climate policy design. With socio-economic uncertainty we refer to different future paths of global population growth, economic output, and development in techno-economic parameters relevant to society. Community efforts by scientists from different disciplines spanning the whole range of climate-relevant research have led to the generation of scenarios describing these paths, harmonizing the analyses of climate mitigation scenarios across studies, and bridging the information flow between the three areas of climate change research mentioned above. Combining well established methods of model-based uncertainty analysis with these scenarios facilitates new methodological approaches for analyzing climate mitigation pathways. An increasing number of studies follows this approach, including the studies contained in the present thesis.

1.2 Structural elements of climate change mitigation research

In this section the framework that contains the research presented in this thesis will be described. First, a short description is provided on how climate change research is divided into three main areas. Then, shifting the focus to climate change mitigation (the specific area of climate change research discussed throughout the thesis), some of its structural elements are briefly discussed.

Climate change research is divided in three main areas. Area I deals with the physical science behind climate change: greenhouse gases (GHG) and aerosols in the atmosphere; temperature changes in the air, land and ocean; the hydrological cycle and changing precipitation (rain and snow) patterns; extreme weather; glaciers and ice sheets; oceans and sea level; biogeochemistry and the carbon cycle; and climate sensitivity (a measure of the additional warming caused by a doubling of the CO_2 in the atmosphere).

Area II assesses its natural, societal and monetary impacts, from a world-wide to a regional view, looking into ecosystems and biodiversity, and humans and their diverse societies, cultures and settlements. It considers their vulnerabilities and the capacities and limits of these systems.

Finally, area III explores the solution space towards stabilizing the Earth's temperature. It addresses all aspects of mitigation including technical feasibility, cost and the enabling environments that would allow measures to be taken up. Enabling environments cover policy instruments, governance options and social acceptability. Synergies and trade-offs with adaptation measures are of increasing interest as are co-benefits, risks and links to sustainable development.

The IPCC, an independent, international, Nobel-prize-winning body of scientists formed by the UN and the WMO issues assessment reports on climate change periodically. The IPCC consists of three working groups, matching exactly the topics of the three areas mentioned above. The IPCC does not conduct its own research, it rather brings together the current available knowledge in the form of periodical assessment reports aiming to assist decision-makers in understanding and dealing with climate change.

1.2.1 Economics of climate change mitigation

The field of economics of climate change mitigation deals with questions such as

- what investments are needed to solve the climate externality/curb GHG emissions in an efficient way?
- how high is the cost of saving the climate?
- how does climate stabilization interact with economic growth?
- how does climate policy interact with broader sustainability?
- what policy instruments are more efficient in decarbonizing the economic system?

In the following, selected topics that deal with these questions and are relevant to the research presented in the current thesis are discussed.

1.2.1.1 Market-based policy instruments

Economic theory suggests that market-based instruments—as opposed to command-and-control policies—are more efficient in achieving environmental goals. Here, the concept of *carbon price* plays a central role. It represents a tax on every CO-emitting activity, or the price of an allowance to emit one tonne of CO_2 in a cap-and-trade system. The latter is a system where, given a fixed amount of overall emissions allowed in a certain period, emitters are endowed with allowances to emit. These allowances can be traded, or emitting firms can invest in cleaner production. It is thus a system where the quantity is fixed and the price is determined by the market. In the case of a carbon tax, i.e. a fixed carbon price, it is the quantity that will be determined by the market dynamics. Beyond market-based economic policies, such as efficiency standards, technology support, etc., gained a lot of attention in recent years when it started becoming evident that market-based instruments alone will not be sufficient to stabilize the climate in the scale and speed that is needed for remaining in safe planetary boundaries (Bertram et al., 2015).

1.2.1.2 The price of carbon and its social cost

But even when investigating the carbon price alone, its exact value and trajectory are of great interest and still highly debated (Strefler et al., 2020; Rogelj et al., 2019). Economic theory suggests that the carbon price should be equal to the *social cost of carbon* (SCC, i.e. the monetized net present value damage from the emission of one additional tonne of greenhouse gas equivalents into the atmosphere). Yet, the prerequisites for this equality to hold are almost impossible to achieve, as perfectly functioning markets and a correct calculation of the SCC are required. Markets are not perfect and the SCC tends to be very sensitive to the choice of time preference (Arrow et al., 2013) valuing future vs. current welfare, which makes its calculation a value-laden decision.

As a result, there is no clear definition of a "correct" SCC. Instead, the carbon price is commonly derived using integrated assessment models running in a so-called cost-effectiveness mode, rather than conducting cost-benefit analyses containing internalized future damages from climate change. Cost-effectiveness studies take climate targets as given, thus containing less trade-offs than cost-benefit analyses. However, hybrid approaches also exist, such as cost-risk analyses (Held, 2019) and least-total-cost studies (Schultes et al., 2020). All studies in the present thesis are cost-effectiveness studies. Another source of debate around the carbon price is found in the study of regional disparities in ambition, ability, and responsibility to act against climate change. The topics range from the effect of a globally uniform carbon price and of inter-regional climate-related monetary transfers on the sovereignty of national states to the amount and structure needed for a proper "climate finance" between developed and developing countries (Bauer et al., 2020).

1.2.1.3 New approaches to established concepts

The economic theory around climate change evolves constantly as the understanding of the problem progresses. Widely spread concepts are being updated to account for recent developments in research. An example is the use of the Hotelling rule (Hotelling, 1931) for the optimal pricing of a non-renewable and non-augmentable resource. The Hotelling rule suggests that the optimal trajectory for the price of a non-renewable and non-augmentable resource should follow the discount rate, and has been widely used in the literature for designing optimal carbon price paths. This has been challenged recently as the availability of technologies that generate negative emissions makes the remaining carbon budget non finite.

Another notable area of fast advancements is the topic of optimal investment across time. Using methods to account for levelized costs of carbon (i.e. accounting for system path dependencies, see Vogt-Schilb, Meunier, and Hallegatte, 2018), as opposed to static marginal abatement cost representations, options that look expensive in the short term turn out to be the ones that would make the most reasonable investment in the long run. An example is the power sector, which features high prices currently, but is expected to dominate the energy sector and become the cheapest source of energy (Luderer et al., 2021).

1.2.1.4 Further topics

Further topics include the separation of policies targeting the demand and supply side (Creutzig et al., 2018) and the consideration of the characteristics of individual sectors of the economy, e.g. land-use (Popp et al., 2011), buildings (Levesque et al., 2018), industry (Broeren, Saygin, and Patel, 2014), and transport (Pietzcker et al., 2014; Wenz et al., 2020). Of particular interest is the interaction of climate policies with the general sustainability perspective (e.g. the Sustainable Development Goals), see .e.g Bertram et al., 2018; Burke et al., 2016, as well as the role of climate change in the topic of global inequality (King and Harrington, 2018), e.g. developing versus developed countries, or different income levels in the population of single regions/countries.

1.2.2 The need for scenarios

Scientists working in the three research areas of climate change (see section 1.2) interact and exchange information, as a result of cross-topic cause-effect chains and feedback loops starting with economic activity that generates emissions which change the climate and affect ecosystems and humans. In order for the research communities related to the physical science, impacts, and mitigation areas to interact effectively, the different scenarios generated in each area have to be compatible with each other. Further, given the vast amount of research output that needs to be processed by each of the IPCC working groups each time assessment reports are released, every report takes several years in the making. Early scenarios were generated sequentially which was leading to substantial delays in the information flow between the working groups (Moss et al., 2010).

Newly developed scenarios aim to tackle these issues, by allowing for a harmonized and parallel—as opposed to sequential—scenario development among the working groups. The climate mitigation working group uses the Representative Concentration

Pathways (RCPs) and the Shared Socio-economic Pathways (SSPs) to achieve this. The SSPs (O'Neill et al., 2014) describe five self-consistent storylines of possible economic and social development for the current century (Riahi et al., 2017). These storylines span the available uncertainty ranges in terms of economic development, population growth, etc. As such, they provide an excellent basis for uncertainty analysis of climate policy. Furthermore, research has identified economic growth and technology availability as important sources of uncertainty in future GHG emissions, and consequently, climate mitigation pathways (Marangoni et al., 2017). Given the large amount of models and modeling teams, and the need for harmonization of the assumptions that policy studies are based upon in order to better inform stakeholders, another category of scenarios—complementary to the SSPs—has been developed, the Share Policy Assumptions (SPAs, Kriegler et al., 2014). The SPAs prescribe climate policy paths and provide a tool for effectively combining the SSPs with the RCPs in exploring the scenario space.

1.2.3 Models

Computer-based simulations play a central role in all three areas of IPCC's research. These simulations are run by mathematical models, describing physical and socio-economic processes. The variety of models and modelling approaches among the three groups of the IPCC and among the various research groups on climate change globally is immense, and this is another reason why harmonization of scenarios among models (and across IPCC groups) is important.

1.2.3.1 Physical science models

General Circulation Models (GCMs), often divided into Atmospheric General Circulation Models (AGCM) and Oceanic General Circulation Models (OGCM), in combination with models for land and sea-ice are the basis of the modeling work in the first group of the IPCC. They are completed by satellite observation and other types of data. The output of these models is used to predict and explain future climates and other earth system processes, and to calculate important measures like the climate sensitivity and the remaining carbon budget (amount of greenhouse gas emissions in gigatonnes) for certain global temperature or radiative forcing (the difference between solar irradiance absorbed by the Earth and energy radiated back to space, commonly used as a measure for global warming) thresholds.

1.2.3.2 Impact models

Impact models take the output of earth system models as input and explore the consequences of disturbed physical processes on human and natural systems various sectors (i.e. agriculture, forestry, water resources etc.). The multi-faceted nature of these impacts and the difficulty in monetizing them are among the challenges that impact modelers are facing. Further, these models are exposed to extreme uncertainties. The newly established UN's Sustainable Development Goals provide an excellent framework for the understanding and categorization of impacts.

1.2.3.3 Energy-economy-climate models

The focus of the present thesis will be on climate mitigation pathways, which are based to a large extent on results from energy-economy-climate (EEC) models (like e.g. the REMIND model used in the present thesis, see Luderer et al., 2015), referred to as integrated assessment models (IAMs) when they consider also land-use change. These models use techno-/socio-economic data and trends as inputs, and derive—among others—energy system configurations and the resulting GHG emissions, based on criteria such as optimal future global (or for major world regions) consumption paths or least-cost energy (or land) systems. EECs, ever increasing in technological detail and policy- and economic realism (e.g. with sectoral detail), rely on scenarios such as the SSPs to cover the uncertainty space and give adequate information to the public, stakeholders etc. Further, results from EECs are often used in international model-intercomparison projects, for better coordination between researchers, tackling uncertainty, and more understanding of the insights delivered by EECs (Tavoni et al., 2013; Kriegler et al., 2014; Luderer et al., 2018; Bauer et al., 2018).

Economic system representation
In terms of the representation of the economic system, EEC models can be classified into general equilibrium models and partial equilibrium models. The former cover all economic sectors and derive a solution where all markets are cleared, whereas the latter derive their solution based on criteria such as the least economic cost of an aggregate measure, e.g. total agricultural production costs. EECs are often soft-coupled with models generating socio-economic trends, like population and energy demand scenarios.

A well established concept in the economic representation of EECs is the structure of a function-tree consisting of nested constant-elasticity-of-substitution (CES) production functions. At the top level, usual inputs to the production function are energy services, labor, and capital, generating economic output (gross domestic product) that can be either saved, invested, or consumed. The part that is consumed is directly aggregated over time to derive intertemporal welfare. The invested part can be used either for investment in generic macroeconomic capital, or for energy investment. The lower parts of the CES tree feeding into the upper most level can be divided into economic sectors (in REMIND these are: buildings, industry, and transport). The exogenous demand for final energy by sector (and sub-sector) and economic output scenarios are derived by soft-coupled models analyzing socio-economic trends.

Solution algorithms
Another classification can be done in terms of the solution algorithm in the temporal dimension, i.e. time. Models are described as recursive-dynamic if they solve time period after time period, whereas intertemporal models compute a solution for the complete time horizon of the problem at once. In the context of intertemportal optimization the concept of *perfect foresight* emerges, which describes the situation of a decision-maker that instantly "knows" the outcome of their current and future decisions. Perfect foresight plays an important role in studies on uncertainty, and methods for accounting for uncertainty have to effectively overcome this limitation (more on this in paragraph 1.3.3.1).

Energy system representation
The energy part of EEC models (e.g. of REMIND) often features high granularity in terms of the available technological options for energy conversion. These include renewable energy sources, fossil resources, nuclear power, geothermal energy, but also more advanced technologies such as hydrogen, synthetic fuels, carbon capture and storage, negative emissions technologies, biofuels, batteries, smart electricity grids etc. To capture real world dynamics, full accounting of energy capacity vintaging is used, combined with real-world data from data providers like the International Energy Agency (IEA) or the International Renewable Energy Agency (IRENA). Technological learning (i.e. the reduction of investment cost of new technologies with increasing installed capacity) is also parameterized and included in most models. Further, to realistically model energy investment and deployment, adjustment costs are taken into consideration. These costs help regulate the speed of generation of energy capacities by respecting economies of scale. At the same time, energy capacity can be removed before the end of its lifetime if it is considered uneconomical (e.g. in the presence of stringent climate policy).

1.3 Uncertainties of climate change and solution approaches

In this section an overview of uncertainty in the context of climate change with a special focus on mitigation will be given. A definition of related terms is provided, followed by common methods to solve problems including uncertainty, while the chapter finishes with typical examples of topics where uncertainty usually arises. This discussion provides the foundation of the three main chapters of the present thesis.

1.3.1 Introduction - Uncertainty classification

A common classification of uncertainty happens with the distinction between *stochastic/aleatory* uncertainty (the persistent randomness of the observed/modelled system due to unresolved processes) and *epistemic* uncertainty (due to things one could in principle know but do not in practice). There are various kinds of epistemic uncertainty, the incomplete knowledge of model parameters is called *parametric uncertainty* (Golub, Narita, and Schmidt, 2014). Another one is structural uncertainty, e.g. when comparing results from different models with different structures. The studies of the present thesis mostly deal with parametric uncertainty.

Uncertainty is often referred to as *risk*, depending mostly on the context (e.g. finance or energy-economy studies). There are concepts related to uncertainty analyses that are central to the idea of dealing with the unknown, i.e. deriving optimal strategies under uncertainty. One such concept is the agent's risk aversion, which describes a measure of the sensitivity of the decision-maker(s) to an incomplete knowledge of the parameters of a system and consequently affects their chosen strategy. In typical energy-economy-climate models this parameter is by definition coupled to a parameter describing the preference of the decision-maker towards a smooth optimal consumption path. This has an impact on uncertainty analyses with energy-economy-models (Lorenz et al., 2012), but disentangling these two parameters would mean completely changing the intertemporal character of the objective function (Traeger, 2009). Further, the concept of *learning* describes the impact and value of updated information about these parameters and can also have a great impact on the optimal strategy (Lara and Gilotte, 2009; Baker, 2006). Finally, in many cases the derivation of such an optimal strategy will mean expressing it in terms of the *expected value* of some metric, based on a known probability distribution of the uncertain parameter.

1.3.2 Methodological approaches to uncertainty analysis

As mentioned above, due to large uncertainties, climate change research is often scenario-based. The scenarios used do not try to predict the future, but rather spell out *possible* futures. After possible scenarios have been identified (usually by expert elicitation (see e.g. Baker et al., 2015; Bosetti et al.; 2015) or by a process like the SSP process), uncertainty analysis methods can be applied to explore the uncertainty space. A classification of important uncertainty analysis methods for scenario-based modelling can be done into two main categories. The first category involves methods that analyze the scenario space either selectively or more extensively, but in both cases derive more than one optimal solutions. The second category consists in deriving one single solution that explicitly accounts for the uncertainty in model inputs. This single solution path is also called *hedging strategy*.

Further differences between the two categories are the computational and conceptual complexity, as well as the applications for which they are mostly used. The first category contributes mainly to the field of *uncertainty propagation*, giving insights into the sources of uncertainty and quantifying it, whereas the second method is more suitable for *decision-making under uncertainty* (Kann and Weyant, 2000).

1.3.2.1 Uncertainty propagation

Typical examples of the first category are *scenario analysis* and *sensitivity analysis*. Scenario analysis consists in performing one simulation for each available storyline (one-factor-a-time methods) described by a scenario table of parameter input values, whereas sensitivity analysis is broader and involves running one simulation for several distinct input parameter values, and combinations thereof, based on probability density functions and a multitude of available *parameter sampling methods*. Methods for efficient handling of the exponentially increasing dimensionality of the problem are constantly being developed and improved, involving methods such as Monte Carlo, Gaussian quadratures, etc.

1.3.2.2 Decision-making under uncertainty

The second category contains conceptually more complex methods such as Discrete Stochastic Programming and Dynamic Stochastic Programming, among others. These methods are more difficult to implement than those of the first category, as they require not only high amounts of computational resources, but also algorithmic intervention to the model. They do, however, greatly assist decision-making by deriving single optimal paths instead of numbers of paths equal to the number of different possible scenarios, as the methods of the first category do. Discrete Stochastic Programming consists in exposing the decision-making process of a model (e.g. the social planner) to all possible values of an uncertain parameter at the same time, thereby allowing for only one possible optimal solution. The method to do so consists in the introduction of different states-of-the-world, each one corresponding to a different discrete value of the parameter, and formulating the objective function of the model in a way that it solves for the *expected* value of e.g. utility, based on given probabilities for the realisation of any of the states-of-the-world. These probabilities can take any form and this is what gives the method the characterization *stochastic*. Dynamic Stochastic Programming is used in multi-stage decision problems and involves a parameter showing stochastic behavior across the temporal dimension, it is thus more suitable for stochastic/aleatory uncertainty. Finally, methods exist that offer the decision-maker tools that derive *robust* strategies under uncertainty, these methods are characterized as Robust Decision-Making (Lempert et al., 2006; Hall et al., 2012).

1.3.3 Sources of uncertainty

1.3.3.1 Regulatory uncertainty

Regulatory uncertainty is the term describing missing information about the evolution of current—and announcement of new—measures to mitigate climate change by governments. An example is the permit price in the European Emissions Trading Scheme: the volatility observed is coupled to policy announcements. Given the importance of the energy sector in GHG emissions, capturing investors' behavior is crucial for the analysis of optimal energy investments under regulatory uncertainty about climate policy. However, when using a typical energy-economy-climate (or integrated assessment) model, i.e. in a general equilibrium framework, the low share of the energy sector in the total economic output makes the welfare effects from regulatory uncertainty negligible from the social planner point of view, but the optimal investments surely remain significant from an investor's perspective.

A metric for the effect of regulatory uncertainty
The crucial question is whether the general equilibrium modelling framework can reflect the investors' risk aversion, the result of which would be a hedging strategy (i.e. a drop or rise in emissions compared to the deterministic case). In the case of uncertain regulation of carbon emissions this will be reflected in a different energy investment—and consequently emissions—path followed in the decision-under-uncertainty framework than in the learn-then-act (deterministic) case. More concretely, if the optimal path under regulatory uncertainty differs from the one

followed when the best guess value of the uncertain parameter (here, the level of the carbon tax is used as a proxy for regulatory uncertainty) is realized in deterministic mode (the best-guess case), then a hedging strategy is observed. To illustrate this, we define a metric for the conditions for appearance of hedging. Let $\hat{U} = \sum_s \eta_s U_s$ be expected utility, while s denotes the state-of-the-world (each state-of-the-world describes the whole system given a certain value of the uncertain parameter, see Appendix for more information) and η_s is the probability of each of the n states-of-the-world. Then, for a typical diminishing marginal utility (i.e. the utility takes a logarithmic form: at higher consumption levels, marginal consumption results in less marginal utility than in low consumption levels) based on per capita consumption we get:

$$\hat{U} = \sum_s \sum_t e^{-\rho t} P \ln \frac{C_s}{P} \quad , s \in [1, ..., n] \tag{1.1}$$

where P is population (assumed equal in all scenarios), t is time, ρ is the pure time preference rate (basically the rate in which future utility loses its present value), and C_s (consumption in each state-of-the-world) is given by:

$$C = Y - I - E_E - ET \quad . \tag{1.2}$$

In Eq. 1.2, Y is total income, I are are investments in the general good, E_E are energy expenditures and E are emissions, which are multiplied by the carbon tax T. Y is considered equal across all scenarios (climate policy does not have a large effect on GDP) and I_s, E_{Es} are equalized by definition (the decision variables have to be equalized across the states-of-the-world, see Appendix). Using a second degree Taylor expansion for the logarithm:

$$\ln(x + dx) \approx \ln x_0 + 2\frac{dx}{x_0} - \frac{dx^2}{2{x_0}^2} - \frac{3}{2} \tag{1.3}$$

and combining Eqs. 1.1, 1.2, and 1.3 we get:

$$\hat{U} = U_{BG} - \mathrm{VAR}(ET) \quad . \tag{1.4}$$

Here, U_{BG} denotes the utility in the deterministic case, while the term VAR is the difference between the decision-under-uncertainty case and the deterministic case, given by:

$$\mathrm{VAR} = \sum_t \left[e^{-\rho t} \frac{P}{2(Y-1)^2} \left(\sum_s \eta_s E_s T_s - E_{BG} T_{BG} \right) \right] \tag{1.5}$$

Due to the low share of the energy sector on total output, the VAR term is negligible. This shows that for the case of an uncertain future carbon tax T the effect can not be large and the optimal solution under uncertainty will coincide with the optimal deterministic solution calculated with the best guess value of the uncertain parameter. If we use the same metric to quantify the effect an uncertain GDP path will have, the effect could be larger. In this case the VAR term takes the form $\mathrm{VAR}(Y) \equiv$

$$\sum_t \left[e^{-\rho t} P \left(\frac{1}{\eta} \sum_s \frac{Y_s}{2(I+E_E)} \left(2 + \frac{Y_s}{2(I+E_E)} \right) - \frac{Y_s}{2(I_{BG}+E_E)} \left(2 + \frac{Y_{BG}}{2(I_{BG}+E_E)} \right) \right) \right] . \tag{1.6}$$

This leads us to the conclusion that the general equilibrium model is more suitable for analysing the broader issue of socio-economic uncertainty, rather than regulatory uncertainty alone. To capture the latter a partial equilibrium model would be needed, e.g. a stochastic stand-alone REMIND (Luderer et al., 2015) energy system model.

A different approach to regulatory uncertainty
A common method to overcome these difficulties and derive optimal solutions under regulatory uncertainty is the method of fixing the decision variables of a time-dependent (mostly inter-temporal) model to their optimal values in the absence of a policy signal (calculated by an additional model simulation), up to the point that a climate policy is announced. Their optimal values after the announcement of the climate target (or, e.g. carbon price) are the optimal values under uncertainty. The method is easy to apply algorithmically and falls under the category of scenario analysis mentioned above, i.e. it derives one optimal path for each different value of the uncertain parameter.

The Paris Agreement as regulatory framework
The regulatory uncertainty around climate change has been greatly reduced with the Paris Agreement (UNFCCC, 2015), a milestone in decades of international efforts to achieve common ground in combating climate change by the international community. The agreement, signed in December 2015 by almost all nations, foresees the announcement of national pledges to be fulfilled in the years to come (until the year 2030 in most cases). This provides a relatively robust regulatory framework that can be used in studies analysing the ambition and impact of climate policies and derive useful conclusions on possible outcomes and potential emission gaps, i.e. remaining efforts still needed in order to follow a pathway leading to acceptable temperature change by the end of the century.

1.3.3.2 Socio-economic uncertainty

With the term "socio-economic uncertainty" we refer to different possible future paths of global population growth, economic output, and values of energy/land-use related techno-economic parameters relevant to society. Given socio-economic uncertainty, choosing the optimal climate policy among possible pathways is not obvious as compared to e.g. an uncertain climate sensitivity, since the baseline (i.e. the reference pathway) to which climate impacts and mitigation costs are compared to is itself uncertain. The following three chapters explore different approaches to tackling socio-economic uncertainty in climate change mitigation studies.

1.3.3.3 Uncertainty in natural phenomena

An argument that speaks against taking immediate action on climate change could be the commonly used financial risk reduction strategy of "wait-and-see", where a decision-maker may wait until the uncertainties around the problem at hand have been reduced with updated incoming information. But in the case of climate change, given potential extreme and irreversible damages, this strategy is rejected for being too risky, see also (Weitzman, 2009). Typical sources of uncertainty include the above-mentioned climate sensitivity, as well as the conditions leading to several natural "tipping points", i.e. natural systems prone to suffer an irreversible shift to a new equilibrium due to increased global mean temperatures.

1.4 Thesis outline

The outline of the thesis is the following: the underlying theory and research is spelled out in the introduction, while in the second chapter we analyze optimal climate policy under explicit accounting of economic growth uncertainty. In the third chapter we proceed to discussing the effect of technological uncertainty on the costs of climate change mitigation. In a final step, in the fourth chapter, we explore how socio-economic uncertainty could influence the optimal burden sharing of climate change mitigation among world regions. The fifth chapter summarizes and concludes. Figure 1.1 provides a visualization of the spatial and thematic coverage of the studies included in the present thesis.

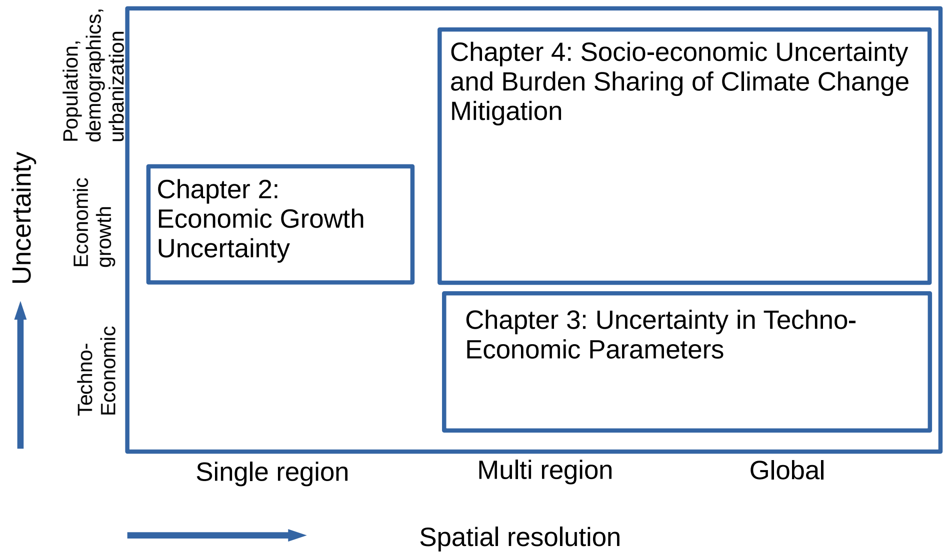

Figure 1.1: Graphical representation of main chapters. The graph shows the spatial and uncertainty coverage of the main chapters of the thesis.

1.4.1 The effect of economic growth uncertainty on climate policy

Starting at the regional level, the effect of economic growth uncertainty on optimal climate policy is discussed in detail in chapter 2. How important is the effect that economic growth has on future emissions, and subsequently, climate targets? The applied method goes beyond simple scenario or sensitivity analysis by explicitly accounting for growth uncertainty using a stochastic version of an energy-economy-climate model. Since intensity targets are considered as means to hedge (i.e. dampen potential negative effects) against this uncertainty, the study leads to a multi-criteria comparison (numerically and analytically) of absolute versus intensity emission targets for the world's largest emitter (China). China's main Paris Agreement pledge is formulated as an emissions intensity target.

1.4.2 The effect of techno-economic parameters on climate mitigation

The energy sector accounts of the highest carbon emissions and at the same time features also the largest decarbonisation potential. Around the globe, rapid changes in economic costs of technologies converting one form of energy to another are being observed. Rapid declines in the case of renewable energy sources and high volatility in the case of fossil fuels such as gas and oil make it nearly impossible to derive solid predictions on their future evolution and role in shaping energy and climate policy. At the same time, different sectors of the economy (buildings, transport, industry) feature different characteristics and decarbonization potentials. These disparities have not received enough attention. Chapter 3 provides a sensitivity analysis of the effect of uncertainty in regionally differentiated techno-economic parameters of energy generation on climate mitigation pathways. Further, a discussion is provided on how economic sectors react to and influence this uncertainty, under different levels of climate policy ambition.

1.4.3 Equity and socio-economic uncertainty

Economic efficiency characterizes all climate mitigation pathways derived with optimization-based (as opposed to simulation models) energy-economy-climate models. Yet, apart from efficiency, the equity dimension needs to be taken into consideration as well. Without equity consideration, future agreements on multilateral action against climate change will be at risk, as developing countries could argue on the basis of Shared but Differentiated Responsibilities and not sign agreements that not foresee a fair distribution of efforts towards climate stabilization. Given the complexity of accounting each region's contribution and role in the overall problem (climate change), several different schemes exist to describe the equity dimension. Each of these schemes addresses one or more equity principles, e.g. capability, equality, responsibility, etc., ultimately describing how the burden of mitigating climate change is shared among world regions. How does the interaction between socio-economic uncertainty and burden sharing of climate mitigation look like? To answer this question and fill a gap in the literature, Chapter 4 provides a global study with regional breakdown, in which we perform an analysis of several different burden sharing schemes across regions, in the presence of socio-economic uncertainty.

2

Economic Growth Uncertainty [*]

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En route to China's mid-century climate goal: Comparison of emissions intensity versus absolute targets

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Abstract

We compare the effectiveness of absolute vs. intensity targets in preparing China for progressively stronger climate action under the Paris Agreement. The Agreement requires countries to submit nationally determined contributions (NDCs) every five years and in addition calls for submission of long-term low greenhouse gas emission development strategies up to 2050. This study conducts a multi-criteria comparison of the adoption of an absolute vs. an intensity interim target in 2030, followed by an absolute target in 2050, for China. In doing so, we explicitly consider economic growth uncertainty as it is the main motivation behind China's and other developing countries' adoption of intensity targets for 2030. We perform the target comparison analytically, as well as using the stochastic version of a large-scale integrated assessment model. The stochastic model is based on expected utility theory and explicitly accounts for uncertainty.

Key policy insights:

- If China wants to hedge against higher than expected economic growth, it is reasonable to adopt an intensity target. However, in case of lower economic growth, this choice becomes problematic as policy costs will rise while the economy grows slow
- The difference in costs due to the 2030 target choice can be of the same order of magnitude as the overall climate policy costs themselves
- An interim absolute target performs better than an equivalent intensity target, under multiple criteria

Keywords: intensity target, economic growth uncertainty, China NDC

1. Introduction

With the contribution of China and India, more than one third of global greenhouse gas (GHG) emissions are currently controlled by targets indexed to future gross domestic product (GDP). This means that, instead of aiming to limit the amount of annual emissions by a given year by an absolute number, China and India are aiming for a reduction in the emission intensity of their economy, i.e. CO_2 emissions per unit of GDP by 2030, as part of nationally determined contributions (NDCs) under the Paris Agreement. China's NDC also contains a target to peak GHG emissions before 2030, but this does not describe an absolute reduction compared to a reference year,

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and could thus lead to different emission pathways depending on how the economy grows. In addition, China's NDC includes two secondary absolute targets for forestry and non-fossil fuel use. In climate policy design, emission intensity targets are used as alternatives to absolute (or quantity) emission targets in order to hedge against economic growth uncertainty, which is particularly large in rapidly developing countries like China and India. At the same time, research (IPCC, 2018; Luderer et al., 2018) shows that the next decade of mitigation action up to 2030 will determine the chances of staying below the warming limits set out in the Paris Agreement. Thus, it is important to explore the implications of the choice of target type in 2030 in preparing the economy and energy system for mid-century (2050) targets, toward the Paris Agreement ambition of holding global mean warming "well below" 2 °C. We do so here for the world's largest emitter, China, applying a state-of-the-art stochastic energy-economy model that explicitly accounts for economic growth uncertainty.

China is currently implementing an emissions trading system, the first one in history formulated with an emissions intensity cap instead of an absolute cap (Goulder et al., 2017). At the same time, its economy is undergoing structural changes (Wang et al., 2019c; Mi et al., 2017a; Lin et al., 2019), thereby reducing its GHG emissions (Guan et al., 2018; Zheng et al., 2019). It is also taking measures to reduce air pollution (Li et al., 2019), and investing heavily in renewables. Yet, these actions alone are not sufficient to rapidly decarbonize the Chinese economy, simply due to the country's sheer size and its dependence on coal, reflecting continued dependence on coal in several emerging economies (Edenhofer et al., 2018; Wang et al., 2019a). While global coal demand dropped in 2015 for the first time this century, the International Energy Agency forecasts that demand will increase again and will not return to 2014 levels until 2021 (IEA/OECD, 2018). Since China currently accounts for 50% of global coal demand—and almost half of coal production—global coal demand in the next decade will depend greatly on the trajectory of China, itself highly uncertain like the future economic growth of China (Lin et al., 2018).

Economic growth is an important indicator to which projected CO_2 emissions are sensitive (Marangoni et al., 2017; Mouratiadou et al., 2016). Economic growth is in turn also affected by CO_2 emissions (Mi et al., 2017b). In the presence of a target indexed by economic growth this effect is further strengthened. It is expected to intensify even more with growing regional rivalry in trade (Neuenkirch and Neumeier, 2015). Motivated by the above, we address the following research question. Under growth uncertainty, does an intensity or a quantity target for 2030 perform better in preparing the Chinese economy for a mid-century target and ultimately a 2 °C pathway? Given that a growth-indexed (intensity) target makes the amount of emissions at the target heavily dependent on economic output, we conduct the analysis to explicitly account for growth uncertainty by deploying a state-of-the-art stochastic integrated assessment model.

The remainder of the paper is structured as follows. Section 2 gives a short overview of how the two target types and target sequencing emerged in the Paris Agreement process, section 3 provides a literature review on the comparison of intensity versus quantity targets, and section 4 describes the scenarios and methods we use for the present comparison. Section 5 begins the target comparison with an analytical method and shows results of deterministic and stand-alone numerical scenarios, which motivate the stochastic analysis on sequential 2030 and 2050 targets under growth uncertainty, on which the final target comparison is based. Section 6 concludes and discusses policy implications. In the SOM, a description of the models and additional methods used in the study is provided, as well as a literature review on uncertainty considerations in energy-economy models of climate change.

2. NDCs and target sequencing after Paris

Under the Paris Agreement, participating countries have announced their NDCs, with most pledging emission reductions up to 2030. Apart from the variation in the level of ambition between countries, there is also a distinction in the chosen types of emission reduction targets. The Paris Agreement calls on developed countries to adopt "economy-wide absolute emission reduction targets", aiming to reduce domestic emissions by a fixed amount compared to a base-year, e.g. 2005 (UNFCCC, 2015). Based on this, many developing countries, including China and India, have chosen to adopt an emission intensity target. This is because an intensity target T hedges against not achieving the desired reduction in absolute emissions E because of unexpected accelerated growth in the economy, as the allowed emissions would increase in lockstep with economic growth Y:

$$T = \frac{E}{Y} \tag{1}$$

An intensity target also helps to avoid "hot-air", which might occur if the absolute target no longer imposed a constraint, because of slow economic growth resulting in lower than expected emissions. With an intensity target, however, the amount of allowed emissions decreases with slower growth (Equation 1). The possibility of hot-air can harm a country's credibility towards other participants of an agreement. Finally, there is also a political stance reflected in the choice of a target indexed to economic output; an acknowledgement that the willingness to act against climate change exists, but is combined with a statement that penalizing growth of developing countries does not correctly reflect the responsibilities associated with historical emissions. Intensity targets are believed to effectively limit economic growth losses from climate policy in contrast to quantity (Pizer, 2005). However, intensity targets are problematic, as they allow emissions to continue to increase(Vuuren et al., 2002), imposing no overall cap. In the case of China and India, which are responsible for over one third of global emissions, the choice of target could have a substantial impact on global decarbonization pathways(Zhu et al., 2015). Progress made in the implementation of NDCs will be monitored and reviewed every 5 years, with a first global stocktake scheduled for 2023. Mid-century strategies are already being discussed, as countries are invited in the decision accompanying the Paris Agreement to submit these strategies by 2020 (UNFCCC, 2015). This means that, once these mid-century targets are in place, the NDCs will, in effect, become interim targets, and a situation of target sequencing will emerge. Compatibility of NDCs and 2050 targets is important and will play a decisive role in paving the way for long term climate stabilization (Pahle et al., 2018; Kriegler et al., 2018). An analysis of the dynamics of this succession of targets under uncertainty is pursued in this study.

3. The literature on target comparison

Intensity targets can be indexed to output or input and are well established in environmental regulation. In the climate change context, they gained more attention when the US decided against ratification of the 1997 Kyoto Protocol (which included absolute targets), and instead took on an intensity target. The debate following the collapse of negotiations at the 2009 Copenhagen Climate Conference—when it became clear that a Kyoto-like global agreement including absolute targets with permit trading was not achievable—has focused on a wider range of national and progressively strengthened commitments.

Overall, the scientific literature on comparison between intensity and absolute targets in environmental regulation can be divided into two main categories: literature on economy-wide regulation, and literature on regulation at firm or sectoral level, see e.g. Quirion (2005). The focus of this paper will be the category of economy-wide regulation, which we divide further into three subcategories: (I) analyses of policies for a specific country or region and discussion of which target performs better; (II) discussions of the implications of the target choice on international bilateral (or broader) agreements in terms of willingness to participate and commit; and (III) target sequencing, i.e. situations where in multi-stage policy design either choice of target can be implemented sequentially.

Marschinski and Edenhofer (2010) discuss (I), (II) as well as (III) using formal analyses with simple analytic models, including also the concepts of hot-air and banking/borrowing of emission permits. They find intensity targets to perform better than absolute targets only under very specific conditions, e.g. a significant positive correlation between shocks in emissions and output. Ellerman and Wing (2003) also touch on all three subcategories, and find hybrid targets including only some reduced form of indexation—which they analyze in detail—to have advantages over pure absolute or intensity targets, but conclude in making the case that willingness to act is more important than the target type.

In the subcategory of single country studies (I), Lu et al. (2013) analyze China's previous intensity targeting for 2020 and conclude that the advantage of flexibility offered by intensity targets is reduced by the prospect of a low growth scenario, which would incur high costs. Wang (2014) calls for a Chinese shift to an absolute emissions cap in order to break the link between emissions and growth. This is based on the grounds of an expected coal import increase under an intensity target following a reduction in coal usage in big coal exporting countries (e.g USA). Zhu et al. (2018) propose a hybrid control scheme based on quantity (energy consumption and CO_2 emissions) and intensity (energy intensity and carbon intensity). Webster et al. (2010) also propose a hybrid instrument consisting of a quantity target combined with a safety valve, and perform a Monte-Carlo analysis for the US economy using a CGE model. They include uncertainty in three parameters: GDP, the rate of autonomous energy efficiency improvement, and the elasticities of substitution of the production functions. Their analysis results in favoring intensity targets depending on parameter values and only in combination with a safety valve instrument. Pizer (2005) makes the case for intensity targets on the grounds of preserving developing countries' right to near-term emission growth.

In the subcategory (II) of interacting participants in agreements, Akimoto et al. (2008) propose a scheme based on sectoral intensity targets, as opposed to country-specific ones, thus reducing the overall energy transformation costs. However, they do not consider the welfare implications and do not account for uncertainty. Dudek and Golub (2003) reject the concept of intensity targets arguing that it could add yet another hurdle to the implementation of already difficult to achieve international agreements.

Authors address the subcategory of target sequencing (III) the least. Sue Wing et al. (2006) find intensity control more suitable under a broad range of emission targets, especially for developing countries. Their analysis is based on two indicators arising from consideration of uncertainty: preservation of expectations and temporal stability.

Here we discuss subcategories (I) and (III) of target comparison studies. We also contribute to the literature on China's climate and energy policy in the post-Paris Agreement era. We do so by explicitly accounting for economic growth combined with short- and long-term climate targets (sequencing), thereby proposing a framework for dealing with these two types of uncertainties. Additionally, in order to address target achievability, the target comparison criteria found in the literature are extended with our multi-criteria analysis.

4. Study design

As growth uncertainty drives the choice of intensity targets, we use methods for explicitly accounting for uncertainty in our modelling. Moreover, to capture the importance of current targets in paving the way for future climate policy we consider target sequencing scenarios. Finally, since reduction of fossil fuel resource use is crucial in shaping China's emissions future, we use a model of large technological detail to capture realistic energy system configurations. We run all scenarios with the integrated assessment model REMIND (Luderer et al., 2015), in its stochastic version called REMIND-S, which is presented here for the first time (the descriptions of REMIND and REMIND-S are found in the Supplementary Online Material (SOM)). An overview of the scenarios considered in our study is given in Table 1. Scenarios unfold in two dimensions: a) Learning about 2050 climate targets, and b) Learning about economic growth. By "learning", we mean the information available to (energy) investors under uncertainty, see also Chapter A.3 of the SOM. Concerning the first dimension we consider the following four scenarios: a no-target scenario (BASE); a scenario (Q50) with a "stand-alone" (as opposed to "sequencing") quantity target in 2050, that assumes learning has already happened in 2010[2], (that is, Q50 is known to the investors); and scenarios with intensity (I30) or quantity (Q30) target types in 2030, which assume that announcement of Q50 happens later than 2010 (target sequencing scenarios) and investors are constrained by their earlier actions after the announcement. The second dimension represents different years where learning about economic growth occurs: 2010 or 2030. Here, "learning in 2010" describes the situation where the investors take decisions accounting for China's best-guess growth path in the period 2010-2030. The different scenario dimensions are explained in further detail below.

4.1. Climate policy scenarios

We define sequencing scenarios as cases with a 2 °C-compatible GHG emissions quantity[3] reduction target in 2050 (mid-century strategy), that has been announced in the year 2030, which we call the learning point. Before the learning point, the investor "sees" only the 2030 target; only for the period after the learning point can decisions be tailored to the updated information (i.e. the Q50 target). To set the stage for these sequencing scenarios we also run "stand-alone" scenarios with the 2030 Chinese climate target formulated as either a GHG intensity target[4]—reflecting the current situation—or an equivalent GHG quantity target (I30 and Q30). Before 2030, the 2050 target is unknown and only a 2030 target exists, reflecting the current level of information. The technique to implement the sequencing scenario in a model with perfect foresight such as REMIND is as follows: a scenario with only the 2030 target (stand-alone scenario) is run in a first step and then the sequencing scenario is optimized

[2] Initial point of the model's time horizon.

[3] Because the long-term goal of 2 °C adopted by the Paris Agreement corresponds to a quantity target (i.e. an absolute limit on cumulative CO_2 emissions), we formulate the 2050 target solely as a quantity target and do not consider 2050 intensity target scenarios.

[4] Our formulation of China's intensity target encompasses also China's peaking target.

over the period 2030-2050 to achieve the mid-century target, with the energy and mitigation investment trajectory fixed to the stand-alone run until 2030. We also consider a hypothetical scenario of full information, where both the Q50 target and growth uncertainty are considered to have been resolved already in 2010 and no interim target in 2030 is needed. This deterministic scenario (Q50-L10-medium) with fixed expectations about economic growth (”medium”) is then used to derive the optimal 2030 interim targets (Figure 1), thereby ensuring that they are aligned with the 2050 quantity target for China, which in turn is fixed to a global below 2 °C scenario based on results from the CD-LINKS project (Kriegler et al., 2018). It is important to note that our calculation of optimal interim targets leads to a more stringent intensity target in 2030 (72% reduction relative to 2005; 0.91 Mt CO_2-e/billion US$2005) than provided in the official Chinese NDC (60-65% reduction relative to 2005), which reflects the fact that the cost-efficient pathway towards the 2050 emission quantity target—and the overall below 2 °C target—typically lies below China’s NDC intensity target in 2030 (UNEP, 2017), see Figure 3. For the comparison of interim target types, we adopt the emissions in 2030 (13.4 Gt CO_2eq, within the uncertainty range found in studies using also national Chinese models like TIMES (Grubb et al., 2015; Roelfsema et al., 2020) of the cost effective mid-century strategy (Q50-L10-medium) as the quantity target (Q30) equivalent to I30.

Climate policy in all scenarios is enforced via an economy-wide lump-sum carbon tax, covering also CH_4 and N_2O emissions, however excluding land-use change[5] CO_2 emissions. The carbon tax takes an initial value in 2020 and then rises with a 5% annual increase. To derive the optimal carbon tax path, the model is solved iteratively (with updating of the initial carbon tax value between iterations) until the climate target, i.e. the reduction of GHG emissions or GHG intensity, is met. Decision variables in REMIND are investments in the macroeconomic capital stock as well as into energy generation technologies (optimal allocation). Technological change is an important driver of the evolution of energy systems. For mature technologies, such as coal-fired power plants, the evolution of techno-economic parameters in the production function of REMIND is prescribed exogenously. For less mature technologies with substantial potential for cost decreases via learning-by-doing, investment costs are determined via an endogenous one-factor learning curve approach that assumes floor costs. In the presence of a national target, a carbon tax is used so that the optimal investments shift to cleaner energy sources, but REMIND fully accounts for path dependencies (e.g. past investments in power plants that have not yet reached the end of their lifetime), as well as increasing marginal costs in the case of rapid expansion of technologies (adjustment costs).

4.2. Economic growth scenarios

The SSP2[6] ”middle-of-the-road” GDP path (Kriegler et al., 2014) is our central, medium growth scenario. Then, by increasing labor productivity[7]—the main driving force of economic growth in the REMIND model (Luderer et al., 2015)—by 25% and by decreasing it by 25% we generate the ”High” and ”Low” scenarios. All three scenarios are assumed to have equal probability. Figure 2 shows the resulting baseline GDP paths for China. For comparison, current growth estimates from other sources—SSP1, SSP5, OECD, and Price-Waterhouse-Coopers—are also shown.

[5] These are also reduced in policy scenarios, but by prescribed scenarios.

[6] Shared socio-economic pathways (SSPs, O’Neill et al. (2014)).

[7] By designing the growth scenarios via labor productivity—rather than directly prescribing GDP paths—we capture macro-economic effects of different policy choices.

Table 1: Overview of the scenarios considered. There are 2 dimensions in the study, reflected in the scenario names as follows: "Climate target(s)"-"Year where learning about growth uncertainty occurs". Example names: Q50-L10 means stand-alone quantity target in 2050 (i.e. no 2030 target) - learning about growth in 2010, I30-L30 denotes a sequencing scenario with intensity target in 2030 and quantity target in 2050 - learning about growth in 2030, etc. In cases where the focus is on a particular growth scenario (low, medium or high), it will be added to the scenario name as follows: Q50-L10-medium. Notes: The 2050 target is formulated solely as a quantity target, because the long-term 2 °C target is also of the same kind.

			Economic Growth	
		2030 Target	**Learn 2010**	**Learn 2030**
2050 Target	**No Target**	**No Target**	BASE-L10	BASE-L30
	Stand-alone	**No Target**	Q50-L10	Q50-L30
	Sequencing	**Intensity**	I30-L10	I30-L30
		Quantity	Q30-L10	Q30-L30

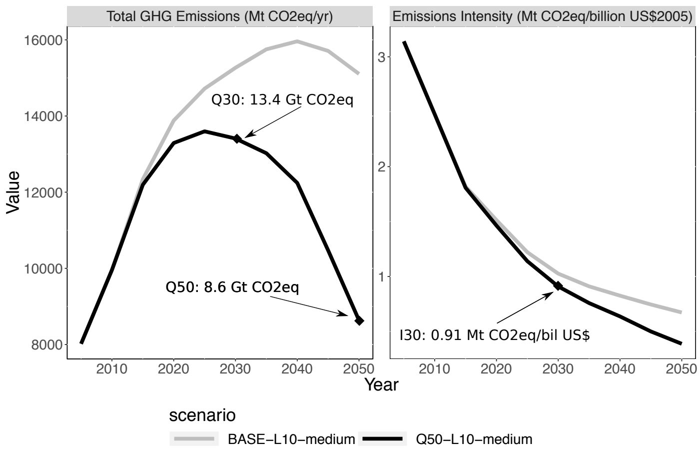

Figure 1: Calculation of China's Q30 and I30 targets, based on **full information**, i.e. medium growth assumptions and full target information. We derive the optimal 2030 quantity target for China (Q30) as well as the equivalent intensity target (I30) from the optimal emissions path of a policy scenario (black line) compatible with the 2 °C long-term target featuring the 2050 cost-efficient emissions from the CD-LINKS project (Q50) as target.

This illustrates the difficulty of deriving solid predictions of Chinese economic growth (Morgan, 2018; Christensen et al., 2018).

5. Results

5.1. The importance of target type

5.1.1. Analytical results

Here, a discussion is provided on how each target type shapes the optimal carbon price differently. This is important because different incentives and investment dynamics are reflected in the optimal carbon price paths, and subsequently different hedging strategies against uncertainty (e.g. a preventive strategy versus a wait-and-see approach). We will show that when emission intensity decreases with economic growth—as is commonly the case—the target type has a strong effect on how economic growth shapes the optimal carbon price paths, i.e. different

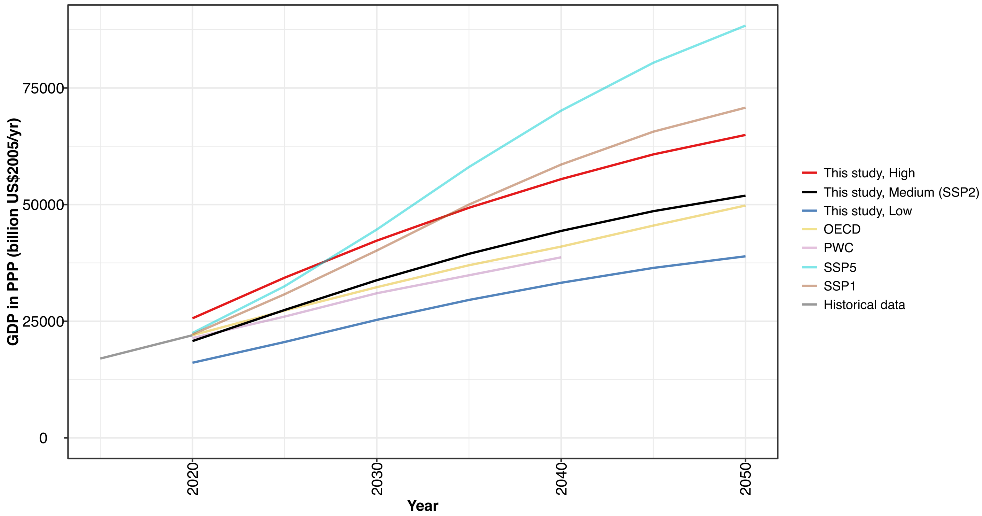

Figure 2: Uncertainty in economic growth of China, measured in purchasing power parity (PPP) GDP. A 25 percent variation around the medium growth scenario (SSP2, O'Neill et al. 2014) is used for the labor efficiency parameter in our scenarios (Low, Medium, High). For reference, SSP1 and SSP5 (based on OECD projections; Kriegler et al. (2017)) as well as other scenarios from the OECD (OECD, 2018), and Price-Waterhouse-Coopers Hawksworth et al. (2017) are shown.

incentives for investment are generated. More precisely, we show that in the presence of a quantity target, the optimal carbon price increases with economic growth, whereas under an intensity target it decreases.

We define the emissions reduction in each case as $\Delta E \equiv E_{base} - E_{pol}$. In a single period setting (stand-alone target), and under an emissions quantity target Q, we obtain (comparing the medium with the low growth scenario):

$$\Delta E_M = E_{M,base} - Q > E_{L,base} - Q = \Delta E_L, \tag{2}$$

because $E_{M,base} > E_{L,base}$ (see Figure 3). Thus, since abatement in the medium scenario is larger than in the low scenario (the target Q is fixed, but baseline emissions are higher under medium growth than under low growth), the medium scenario will feature a higher carbon price.

In the case of an intensity target I, we get (Y stands for GDP):

$$\Delta E_L = E_{L,base} - I \cdot Y_{L,pol} = E_{M,base} \cdot \frac{E_{L,base}}{E_{M,base}} - I \cdot Y_{M,pol} \cdot \frac{Y_{L,pol}}{Y_{M,pol}} > E_{M,base} - I \cdot Y_{M,pol} = \Delta E_M \tag{3}$$

The inequality in eq. 3 holds only if

$$\frac{E_{L,base}}{E_{M,base}} > \frac{Y_{L,pol}}{Y_{M,pol}} \Rightarrow \frac{I_{L,base}}{I_{M,base}} \cdot \frac{Y_{L,base}}{Y_{M,base}} > \frac{Y_{L,pol}}{Y_{M,pol}} \Rightarrow I_{L,base} > I_{M,base} \tag{4}$$

(GDP cancels out because $Y_{base} \approx Y_{pol}$; climate policy has very little impact on GDP). The last inequality of eq. 4 holds for China and most countries, because emissions intensity is commonly reduced faster in a higher growth compared to a lower growth scenario, see Figure 3. Thus from eq. 3 it holds that $\Delta E_M < \Delta E_L$

Summarizing, in the presence of an intensity target the optimal carbon price will be highest for the low growth scenario, as seen also in Figure 4. As the carbon price is a proxy for costs of policies, this has serious implications in how the hedging strategies of the early years are shaped, which we will quantify numerically in the following.

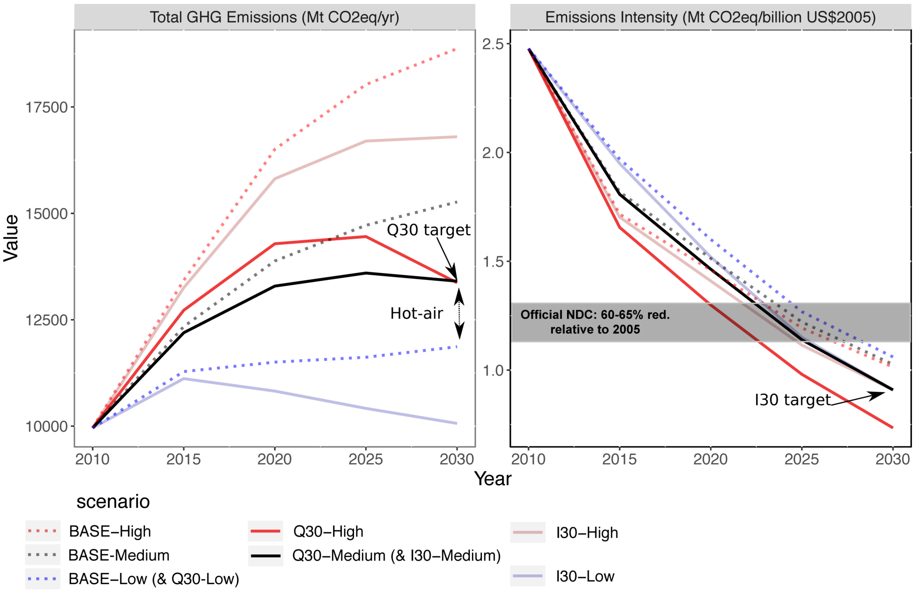

Figure 3: Overview of the deterministic case (learn about growth in 2010). Left: GHG emissions scenarios for China. The 13.4 Gt CO_2eq target is not constraining for the low growth Q30 scenario (hot-air is the difference in 2030 between the dashed blue and the continuous black line), and the indexed target (I30 scenarios) is not unique. Without uncertainty (medium growth) it makes no difference whether an intensity or quantity target is chosen. Right: GHG intensities for the same scenarios. The converging Q30 emission scenarios are now diverging, and the I30 scenarios are converging to our 2 °C-compatible intensity target. The official NDC intensity target of China is depicted in the grey area. It is not imposing a constraint, as it lies above the baseline intensities in 2030. Note: L10 has been omitted from the scenario names

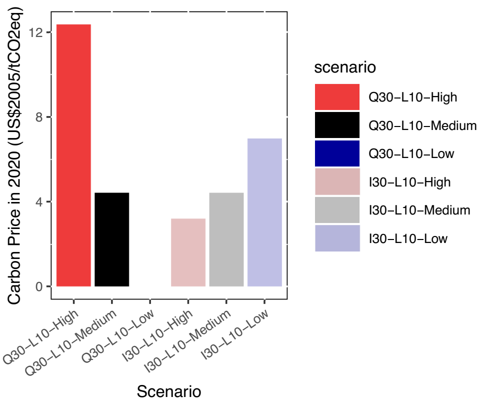

Figure 4: How economic growth scenarios shape the optimal carbon price paths in China, i.e. the policy costs; Q30 and I30 targets have reversed behavior in response to the high and low growth scenarios, whereas they are equal in the absence of uncertainty (medium growth).

5.1.2. Numerical results

To motivate the use of a stochastic modelling framework in the upcoming sections, we start the numerical analysis by investigating the deterministic modelling—i.e. assuming that learning about growth uncertainty has occurred already in 2010, see Chapter A.3 of the SOM—of the targets in 2030. We compare the medium with the high and low growth scenarios, and discuss environmental implications in terms of total GHG emissions. Differences in marginal abatement costs are expressed in terms of carbon prices. Finally, we discuss welfare effects in terms of differences in *balanced growth equivalents* (BGE), as proposed by Stern (2007), and further analyzed and used by Anthoff and Tol (2009), and Drouet and Emmerling (2016), see the SOM for details.

The optimal emissions of the deterministic cases are given in Figure 3. Without uncertainty, it makes no difference whether an intensity or quantity target is chosen, which can be proven also analytically (Ellerman and Wing, 2003). Since we have chosen equivalent quantity and intensity targets for the medium growth scenario, optimal emissions are identical in this case, as seen by the coinciding paths (black line). This is no longer true for the high and low growth scenarios. If a higher than expected growth is observed, emissions in 2030 will be higher regardless of target choice, seen by the difference in the red and the black curves. An intensity target (I30-L10) has increased emissions in total and in absolute value in 2030, whereas a quantity target (Q30-L10) meets the 2030 target of 13.4 Gt CO_2eq but with increased total emissions. In the case of low growth, the quantity target is not imposing a constraint as the baseline emissions are already below it (dashed blue line). The average annual growth rate of GDP in the period 2010-2030 is assumed to be 6.7% in the medium growth SSP2 scenario (historical data: ca. 6.5% in 2017-2020). By conducting a sensitivity analysis of emissions on the GDP growth rate we find that emissions under a quantity target are the same as in the medium growth baseline (i.e. the target is not imposing a constraint) at an average annual growth rate of GDP of 6.1%[8]. The non-constraining target could give rise to hot-air and climate policy costs can drop to zero. In contrast, an intensity target can impose a stringent emissions constraint on a slow growing economy (weak blue line), i.e. an additional challenge.

In terms of marginal abatement costs, Figure 4 shows that under high growth, to reach a quantity target they can increase almost 3-fold, whereas they would decrease under an intensity target. On the other hand, in the low growth case, there is a significant increase in marginal abatement costs for reaching the intensity target, while the quantity target produces hot-air, i.e. no costs (the target is not imposing a constraint as baseline emissions are already below it). Regarding the welfare effects, Table 2 shows how the differences in welfare between target types compare with each other and—for reference—with the costs of climate policy. In the case of high growth, an intensity target performs better than a quantity target, whereas in the case of low growth, only an intensity target incurs costs (as the quantity target is not imposing a constraint), so quantity has an advantage. Our sensitivity analysis of emissions on the GDP growth rate (see Chapter A.6 of the SOM) suggests that these effects are monotonous, meaning that an intensity target has a lower BGE than quantity under low growth already at a marginal variation in GDP growth around the medium scenario (because the intensity target is a "moving" emissions target), and a higher BGE in the case of high growth, which means it provides cost containment compared to a quantity target.

[8] For reference, our low growth scenario features a GDP growth rate in the period 2010-2030 of 5.5%, and the average annual growth rate of long-term OECD projections for 2020-2050 is ca. 2.5%.

Table 2: Comparison of welfare effects until 2030 measured as percent changes in *balanced growth equivalents* (BGE, see the SOM) for the different target types of the stand-alone 2030 scenarios. The last two rows are the corresponding climate policy costs (i.e. comparison with the baseline) for each target and for the same period, which we use for reference.

Scenarios compared	**ΔBGE 2030 (%)**
High growth (I30-L10-High vs. Q30-L10-High)	1.0
Medium growth (I30-L10-Medium vs. Q30-L10-Medium)	0
Low growth (I30-L10-Low vs. Q30-L10-Low)	-0.97
Quantity (BASE-L10 vs. Q30-L10)	0.6
Intensity (BASE-L10 vs. I30-L10)	0.75

In the medium growth case, there is no difference in welfare, due to the equivalence of the two targets in the absence of uncertainty. It is important to note that the differences in welfare between the targets in the high and low growth scenarios could reach the same order of magnitude as the costs of climate policy (last two rows of Table 2). This observation, combined with the case-dependent advantage that each target exhibits—depending on what growth scenario materializes—motivates us to perform the stochastic analysis of the upcoming sections, in order to compare intensity and quantity targets.

5.2. How hedging strategies shape the target sequencing

5.2.1. Target sequencing scenarios

In the remainder of the paper we perform decision-making under uncertainty (see Chapter A.3 of the SOM) with the REMIND-S model, as opposed to the deterministic analysis of the previous section. We do so by performing an expected value welfare maximization across all three growth cases (low-medium-high) at once. We thus derive one single optimal emissions path instead of one for each growth scenario, which is the main feature of the stochastic model. This allows us to identify hedging strategies (hedging strategies are characterized by a lower emissions pathway due to taking into account all three possible economic growth outcomes simultaneously, compared to simply assuming medium growth in a deterministic optimization, see Figure A.1).

The implementation of the stochastic optimization problem describes the situation of an investor who has to decide on a single energy sector investment strategy for the period 2010-2030 until uncertainty about economic growth is resolved. The REMIND-S model also accounts for investments in industrial capital stock as an additional optimization variable. This decision remains freely adjustable to the individual economic growth scenario from 2010 onward, assuming that capital markets can learn immediately about the actual growth path as it unfolds. To implement the target sequencing, we calculate the optimal emission paths for cases where, initially, decisions up to a certain point are taken with only the 2030 targets being known (stand-alone scenarios), and an announcement of a "follow-up" 2050 quantity target taking place in the same year. This myopic behavior describes a situation of unanticipated learning in 2030. We simulate two types of sequencing scenarios, one that follows after the 2030 intensity target case, which is denoted with I30-L30, and one that follows after the 2030 quantity target case, which we denote with Q30-L30 (see also Table 1). REMIND-S calculates the optimal paths that emerge around mid-century, resulting from investment decisions pre-2030 taken under growth uncertainty and without information about the follow-up 2050 target.

In Figure 5, we show how target sequencing shapes optimal emissions paths, and plot these next to the hypothetical, full-information case of the 2 °C compatible stand-alone[9] target in 2050, which we used to derive the optimal 2030 targets. Due to the stronger hedging (i.e. the deviation from the Q50-L10-medium scenario, which we analyze in detail in the next section) in the I30-L30 scenario, decarbonization starts earlier and thus total emissions (area under emissions curve) are lower than in the quantity target case (483 Gt CO_2 in I30Q-L30 vs. 527 Gt CO_2eq in Q30-L30). In Figure 6, a more detailed representation of the same scenarios is shown, focusing on key variables and adding the baseline scenario. An intensity target scenario has a higher net present value (in year 2020) carbon price (27.7 \$/tCO_2 vs. 18.6 \$/tCO_2). This leads to over-investment in energy in the early years (energy investment curve). The 2050 target announcement leads to jumps in the optimal carbon price paths. It can also lead to substantial early retirement of coal capacity in the power sector up to 2050 (aggregated over time) of up to 2500 GW, i.e. nearly 40% of total projected coal capacity in the baseline (6,400 GW), and 66% more than the idle capacity in the quantity target scenario (these estimates are in the lowest range of estimated stranded capacity from Wang et al. (2019a) and Wang et al. (2019b)). Finally, a quantity target could lead to less welfare losses as seen in the *certainty- and balanced-growth equivalent* curves. Figures A.8 and A.9 show further numerical results, including for GDP, energy demand, and energy mixes.

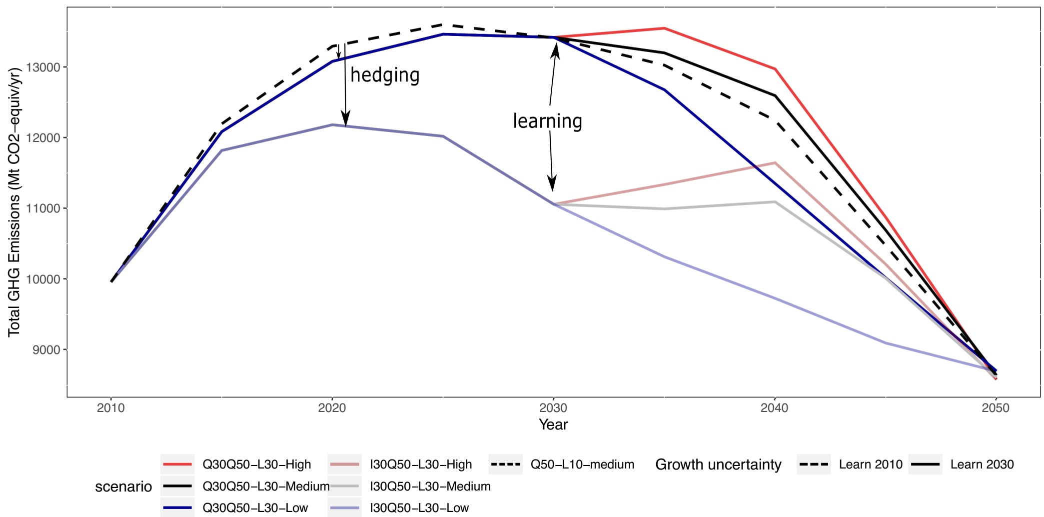

Figure 5: Optimal emissions of the target sequencing scenarios for China (featuring uncertainty about growth and 2050 target until 2030), compared to the stand-alone medium-growth Q50 deterministic scenario (full information about 2050 target and economic growth). In 2030 uncertainty is resolved (learning point) and the 2050 absolute emissions target is announced (myopic behavior). The decisions prior to the learning point are equal across the growth scenarios (one line for each target type) whereas after the learning point they can be tailored to the individual growth scenarios, see Chapter A.3 of the SOM. In the graph the intensity target's stronger hedging is shown.

[9]The Q50-L10-medium scenario features no growth uncertainty, and has full long-term target information; thus an interim target is obsolete.

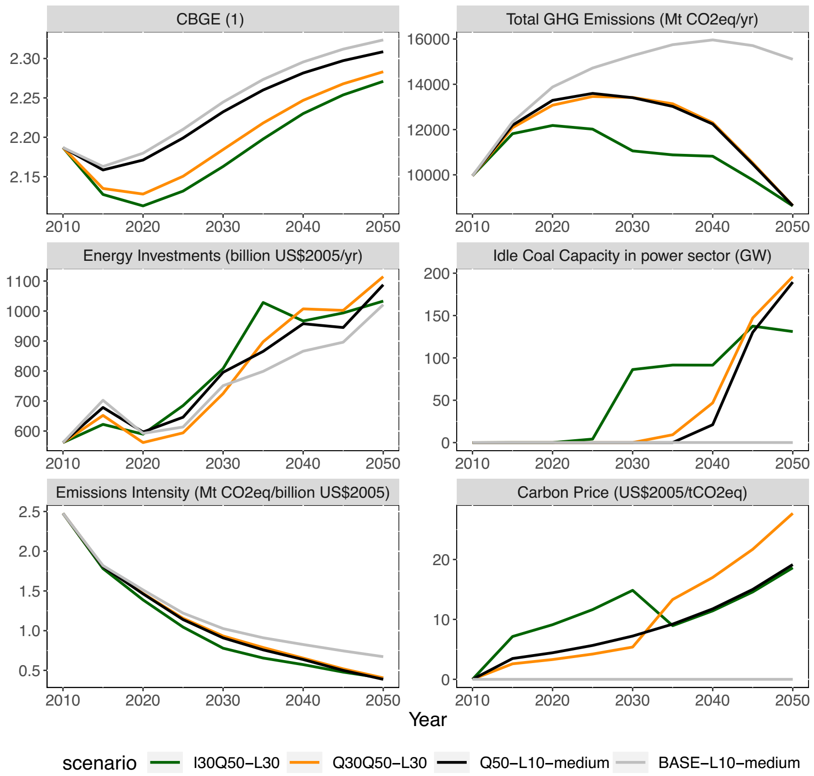

Figure 6: Optimal paths of the sequencing scenarios for China, under uncertainty. The same graphs with each growth scenario plotted separately are found in Figure A.7. CGBE: *certainty- and balanced-growth equivalent.*

Sue Wing et al. (2006) discuss the theoretical property stating that intensity targets lead to a slower decoupling of growth and emissions. In our stochastic analysis, however, where hedging strategies against growth uncertainty are identified, we find that it is the intensity target that could lead to a faster—but more costly—reduction in emissions.

5.2.2. Hedging strategies in the energy system

The sequencing scenarios of the previous section exhibit a different behavior depending on whether the 2030 target is an intensity or absolute target. We showed analytically that this is due to different incentives generated by each target type. With the sectoral and technological detail of REMIND-S we are able to quantify the optimal hedging strategies dictated by the different incentives of the previous sections. Hedging is the result of seeking the best compromise between all the possible growth scenarios, and exists also in the baseline case (see Chapter A.4 of the SOM). However, it unfolds differently in the case of climate targets under growth uncertainty. Under an intensity target the low growth scenario poses a challenge for the economy if realized, as the 2030 intensity target becomes more stringent if GDP grows slowly (see Figure 3). The dominance of the low growth scenario leads to the hedging strategy of further reduced emissions when comparing a full-information with an uncertainty scenario (Q50-L10-Medium vs. I30-L30 in Figure 5), describing a preventive strategy. This happens via increased renewable energy capacity additions in the power sector—alongside increased energy investment in general—compared to the quantity target case (see Figure A.4 for a comparison of energy investment strategies). However, this comes at an increased price for energy, as seen on the same figure. Under a quantity target the hedging strategy differs substantially; now the high growth scenario poses a challenge—due to high policy costs if the target is fixed (see again Figure 3)—and the least-cost possible energy system in the presence of the short-term 2030 target is one characterized by moderate energy investment, pointing to a wait-and-see strategy and less hedging in emissions. This is reflected also in the average price paid for energy, as seen in Figure A.5.

5.2.3. The role of coal

The power sector plays an important role in the transition to a low-carbon economy. In China, this sector is dominated by coal. An illustration of how coal shapes the hedging in emissions is shown in Figure 7, where it is seen that until 2020 in the quantity target scenario optimal coal usage follows a similar path as the deterministic policy case, only to be reduced further under an intensity target. This is not the case for the other two important fossil fuel energy sources, gas and oil, as seen on the same figure. The coal reduction under the intensity scenario is driven by the retired coal capacity in the power sector (see Figure 6 and section 5.2.1).

We examine also the stylized case of anticipated learning about uncertainty, described by the introduction of a learning step in a perfect foresight model like REMIND-S, which greatly reduces the target effect and leads to similar strategies for each target. As seen in Chapter A.4.2 of the SOM, anticipated learning reduces the importance of target choice and leads to almost the same amount of uncertainty-driven emissions reduction for a quantity and an intensity target.

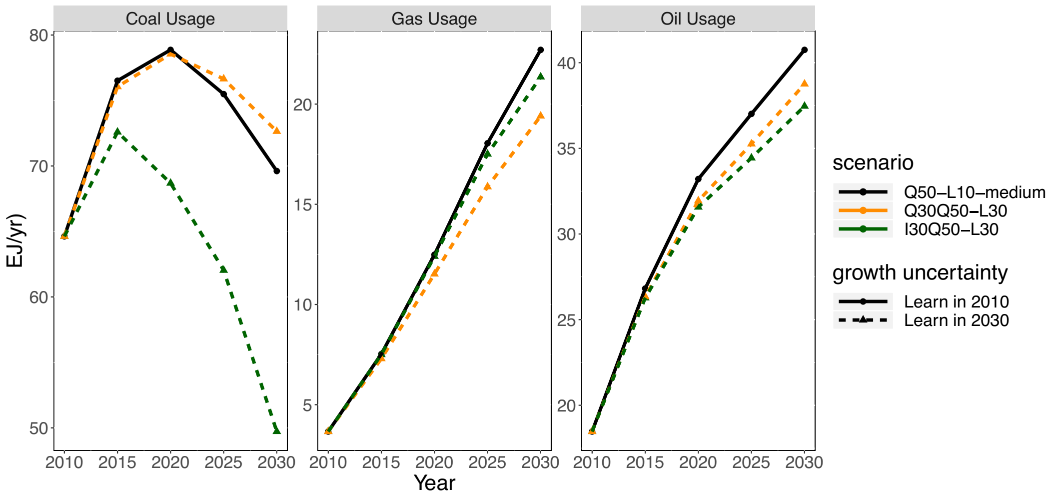

Figure 7: Optimal fossil resource usage in China under uncertainty compared to the scenario of full information. The quantity scenario features no further uncertainty-driven decrease in coal usage whereas oil and gas are reduced.

5.3. Multi-criteria comparison of intensity vs. quantity targets

Climate targets, as policy objectives, need to be evaluated in terms of more than one property to achieve political and social acceptance; climate policy will affect the environment (GHG concentration, air pollution, etc.), but it can also create winners and losers depending on the direction of investment streams. It can even be the reason

Table 3: Overview of criteria for target comparison. A detailed description of the indicators is provided in Chapter A.7 of the SOM.

Criterion	Short description	Category
GHG emissions	Total GHG emissions in the period 2005-2050	Environmental
Carbon price	The size of the carbon price that has to be exerted on the economy for the target to be met	Efficiency
Welfare loss	Indicator based on total discounted social welfare loss until 2050. Measured in *balanced growth equivalents*	Efficiency
Idle coal capacity	Total retired coal capacity in the power sector that has not reached the end of its lifetime	Disruptiveness
Cost volatility	Expressed by the volatility of the carbon price around 2030, the year of learning about the mid-century target	Disruptiveness
Expected Value of Information	Describes the difference in the value of learning about growth uncertainty between the two target types	Expectation Stabilization
Non-optimal investment	The amount by which investment in energy deviates from the medium-growth full-information path	Expectation Stabilization

why capacity is retired earlier than expected (due to unanticipated strengthening of policies), giving rise to sunk investments. Moreover, different target types can give rise to completely different response strategies. For example, a preventive strategy can incentivize high investment in energy early on, whereas a wait-and-see strategy can have the opposite effect. This will affect how costs are distributed over time. Furthermore, as targets will inevitably be sequential, the above-mentioned effects will become more complex, as it is also the type of the second target and the time of its announcement that will play an important role. Lastly, the fact that economic growth cannot be predicted with certainty already affects the baseline case (over- or under-investment), and this effect intensifies in the presence of climate policy.

To address these implications and take into account the findings of the analytical discussion and the deterministic and stochastic analyses, we compare intensity and quantity targets under multiple criteria. We choose four categories of criteria: the **environment**, economic **efficiency** (relating to costs of policies and their distribution over time), **disruptiveness** (relating to abrupt changes in the system caused by the announcement of targets) and **expectation stabilization** (relating to how targets under growth uncertainty affect investors' optimal behavior). Overall, we use seven criteria. Environmental criteria are expressed in terms of GHG emissions, while target efficiency is measured in terms of carbon prices and welfare. As indicators addressing disruptiveness, we use idle coal capacity and climate policy cost volatility. To assess the robustness of targets for stabilizing expectations, we rate them according to the Expected Value of Information (EVOI) and non-optimal investment. The criteria are summarized in Table 3, and explained in detail in Chapter A.7 of the SOM.

Figure 8 illustrates the multi-criteria comparison between a quantity and an intensity target, taking into account target sequencing and growth uncertainty. The quantity target performs better in five out of seven criteria, whereas intensity is better under one. The individual values of the indicators are discussed in section 5.2.1. Regarding the criteria classification, an intensity target leads to slightly lower total emissions but the quantity target features more economic efficiency (lower carbon price and less welfare losses) and favors stabilization of expectations (less non-optimal investment). In terms of disruptiveness, a sudden switch to a quantity target after 2030 could cause significant coal capacity in the power sector to become idle. Under a quantity target the idle capacity would be lower, with the additional benefit of a smaller jump in the carbon price due to the announcement of the 2050 target. In the EVOI case there is no clear advantage of either a quantity or intensity target, highlighting the dominant role of growth uncertainty. The reduction of growth uncertainty largely eliminates the target effect, as shown in Chapter A.4.2 of the SOM. Summarizing, a 2030 quantity target features an easier low carbon transition, e.g. with less costs and less idle capacity in the energy sector. The overall effect of the quantity target performing better can be interpreted as a manifestation of the optimal response to the risk of realization of the low growth scenario in the case of an intensity target, which outweighs the risk of a high growth scenario under a quantity target (because under high growth the extra climate policy costs are more easily borne). It is thus more beneficial to hedge against growth uncertainty with a 2030 quantity target because in the case of low growth it provides cost containment and, at the same time, offers a smoother transition to the mid-century quantity target.

We acknowledge that the absence of indicators relating to interaction with other countries (incentives, cooperation, etc.) and the absence of an indicator based on air quality constitute limitations for our study. To capture these, a stochastic model with regional interaction (and high spatial resolution) would be needed, which currently involves a prohibitive computational burden. Moreover, the model's sensitivity related to the utility function's constant relative risk aversion could be explored in a further analysis.

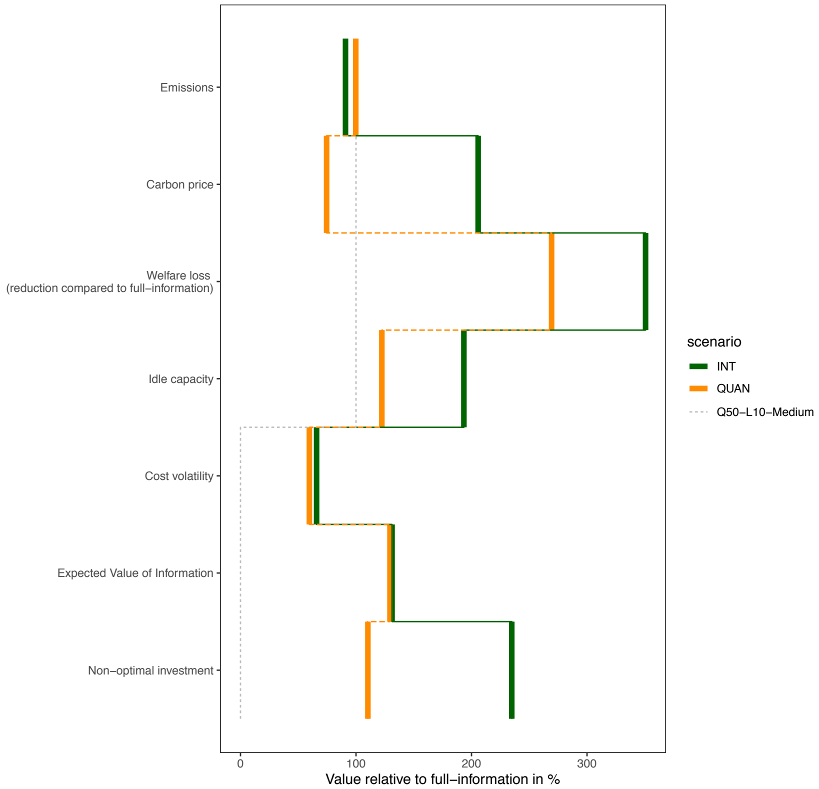

Figure 8: Multi-criteria comparison of quantity and intensity targets for China. Indicators are listed along the y-axis and their values are given on the x-axis as percentages relative to the medium-growth full-information scenario value (Q50-L10-Medium), for harmonization. A lower indicator value indicates a more positive effect, i.e. reduced risk. A quantity target generally performs better than an intensity target. In one case there is no clear advantage for the one or the other type of target (EVOI). Note: the full-information value is 100% for the four upper indicators. For the three indicators at the bottom where scaling with the full-information value is not possible (it is zero by definition), we scale with the respective lower value. A detailed explanation of the criteria is given in Chapter A.7 of the SOM.

6. Conclusions

We performed an empirical study of China's climate policy to assess if its 2030 emission intensity target performs better than an absolute target in preparing the economy for a 2 °C compatible mid-century target, i.e. in a target sequencing situation.

Taking into account all possible growth scenarios, we show that an interim 2030 absolute target *en route* to a 2 °C compatible mid-century quantity target performs better than an intensity target in our multi-criteria comparison for the case of China; costs are lower and it also reduces uncertainty. As an explanation for the advantage of a quantity target over an intensity one, we show analytically that the target type has a strong effect on how growth scenarios shape the optimal carbon price, i.e. different incentives for investment are generated for each target type. The analytic results enhance the robustness of the findings, as the form of the probability distribution describing the uncertainty does not play any role there.

China's climate targets constitute an important part of the Paris Agreement, reflecting the country's key role in the negotiations and the international effort to combat climate change. As such, their performance needs careful analysis both for the sake of China's economy and for a successful agreement. Ellerman and Wing (2003) suggest that—in a theoretical and perfectly flexible system—intensity and quantity targets can be interchanged infinitely and eventually lead to the same costs and emissions. This is challenged here, due to the fact that, in reality, energy investment cycles and power plant lifetimes have time scales longer than the target updating (e.g. China's official 5-year plans, or the Paris Agreement process for mid-century strategies); that is, the system shows inertia rather than flexibility. Consequently, successions of different types of targets will lead to a discontinuity and should be avoided. A strengthening of China's climate ambition is underway, driven by the fact that, in the current 5-year plan, climate targets were easily met through energy saving policies and economic structure adjustments. The adoption of a 2030 absolute target is more suitable for China, as the long-term 2 °C target is also, in effect, an absolute target. The switch from the current interim intensity target to absolute emissions control could happen gradually, taking advantage of the Agreement's updating of targets every five years.

Code and data availability. REMIND is open-source: https://github.com/remindmodel/remind. The source code of the models used (REMIND and REMIND-S) as well as the data are available by the authors upon request.

Declarations of interest: none.

References

References

Akimoto, K., Sano, F., Oda, J., Homma, T., Rout, U.K., Tomoda, T., 2008. Global emission reductions through a sectoral intensity target scheme. Climate Policy 8, S46–S59. URL: http://dx.doi.org/10.3763/cpol.2007.0492, doi:10.3763/cpol.2007.0492.

Anthoff, D., Tol, R.S.J., 2009. The Impact of Climate Change on the Balanced Growth Equivalent: An Application of FUND. Environmental and Resource Economics 43, 351–367. URL: https://doi.org/10.1007/s10640-009-9269-5, doi:10.1007/s10640-009-9269-5.

Christensen, P., Gillingham, K., Nordhaus, W., 2018. Uncertainty in forecasts of long-run economic growth. Proceedings of the National Academy of Sciences 115, 5409–5414. URL: http://www.pnas.org/content/115/21/5409, doi:10.1073/pnas.1713628115.

Drouet, L., Emmerling, J., 2016. Climate policy under socio-economic scenario uncertainty. Environmental Modelling & Software 79, 334–342. URL: http://www.sciencedirect.com/science/article/pii/S1364815216300305, doi:10.1016/j.envsoft.2016.02.010.

Dudek, D., Golub, A., 2003. "Intensity" targets: pathway or roadblock to preventing climate change while enhancing economic growth? Climate Policy 3, S21–S28. URL: http://www.tandfonline.com/doi/abs/10.1016/j.clipol.2003.09.010, doi:10.1016/j.clipol.2003.09.010. 12.

Edenhofer, O., Steckel, J.C., Jakob, M., Bertram, C., 2018. Reports of coal's terminal decline may be exaggerated. Environmental Research Letters 13, 024019. URL: http://stacks.iop.org/1748-9326/13/i=2/a=024019, doi:10.1088/1748-9326/aaa3a2.

Ellerman, A.D., Wing, I.S., 2003. Absolute versus intensity-based emission caps. Climate Policy 3, S7–S20. URL: http://www.tandfonline.com/doi/abs/10.1016/j.clipol.2003.09.013, doi:10.1016/j.clipol.2003.09.013. 34.

Goulder, L.H., Morgenstern, R.D., Munnings, C., Schreifels, J., 2017. China's National Carbon Dioxide Emission Trading System: An Introduction. Economics of Energy & Environmental Policy 6. URL: http://www.iaee.org/en/publications/eeeparticle.aspx?id=175, doi:10.5547/2160-5890.6.2.lgou.

Grubb, M., Sha, F., Spencer, T., Hughes, N., Zhang, Z., Agnolucci, P., 2015. A review of Chinese CO2 emission projections to 2030: the role of economic structure and policy. Climate Policy 15, S7–S39. URL: https://doi.org/10.1080/14693062.2015.1101307, doi:10.1080/14693062.2015.1101307. publisher: Taylor & Francis _eprint: https://doi.org/10.1080/14693062.2015.1101307.

Guan, D., Meng, J., Reiner, D.M., Zhang, N., Shan, Y., Mi, Z., Shao, S., Liu, Z., Zhang, Q., Davis, S.J., 2018. Structural decline in China's CO 2 emissions through transitions in industry and energy systems. Nature Geoscience , 1URL: https://www.nature.com/articles/s41561-018-0161-1, doi:10.1038/s41561-018-0161-1.

Hawksworth, J., Audino, H., Clarry, R., 2017. The World in 2050. Technical Report. PwC.

IEA/OECD, 2018. IEA/OECD – Coal statistics. URL: https://www.oecd-ilibrary.org/energy/data/iea-coal-information-statistics/oecd-coal-statistics_data-00554-en.

IPCC, 2018. Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. Technical Report.

Kriegler, E., Bauer, N., Popp, A., Humpenöder, F., Leimbach, M., Strefler, J., Baumstark, L., Bodirsky, B.L., Hilaire, J., Klein, D., Mouratiadou, I., Weindl, I., Bertram, C., Dietrich, J.P., Luderer, G., Pehl, M., Pietzcker, R., Piontek, F., Lotze-Campen, H., Biewald, A., Bonsch, M., Giannousakis, A., Kreidenweis, U., Müller, C., Rolinski, S., Schultes, A., Schwanitz, J., Stevanovic, M., Calvin, K., Emmerling, J., Fujimori, S., Edenhofer, O., 2017. Fossil-fueled development (SSP5): An energy and resource intensive scenario for the 21st century. Global Environmental Change 42, 297–315. URL: http://www.sciencedirect.com/science/article/pii/S0959378016300711, doi:10.1016/j.gloenvcha.2016.05.015.

Kriegler, E., Bertram, C., Kuramochi, T., Jakob, M., Pehl, M., Stevanovic, M., Höhne, N., Luderer, G., Minx, J.C., Fekete, H., Hilaire, J., Luna, L., Popp, A., Steckel, J.C., Sterl, S., Yalew, A.W., Dietrich, J.P., Edenhofer, O., 2018. Short term policies to keep the door open for Paris climate goals. Environmental Research Letters URL: http://iopscience.iop.org/10.1088/1748-9326/aac4f1, doi:10.1088/1748-9326/aac4f1.

Kriegler, E., Edmonds, J., Hallegatte, S., Ebi, K.L., Kram, T., Riahi, K., Winkler, H., Vuuren, D.P.v., 2014. A new scenario framework for climate change research: the concept of shared climate policy assumptions. Climatic Change 122, 401–414. URL: http://link.springer.com/article/10.1007/s10584-013-0971-5, doi:10.1007/s10584-013-0971-5.

Li, N., Chen, W., Rafaj, P., Kiesewetter, G., Schöpp, W., Wang, H., Zhang, H., Krey, V., Riahi, K., 2019. Air Quality Improvement Co-benefits of Low-Carbon Pathways toward Well Below the 2 °C Climate Target in China. Environmental Science & Technology 53, 5576–5584. URL: https://doi.org/10.1021/acs.est.8b06948, doi:10.1021/acs.est.8b06948. publisher: American Chemical Society.

Lin, J., Fridley, D., Lu, H., Price, L., Zhou, N., 2018. Has coal use peaked in China: Near-term trends in China's coal consumption. Energy Policy 123, 208–214. URL: http://www.sciencedirect.com/science/article/pii/S0301421518305871, doi:10.1016/j.enpol.2018.08.058.

Lin, J., Kahrl, F., Yuan, J., Chen, Q., Liu, X., 2019. Economic and carbon emission impacts of electricity market transition in China: A case study of Guangdong Province. Applied Energy 238, 1093–1107. URL: http://www.sciencedirect.com/science/article/pii/S0306261919301515, doi:10.1016/j.apenergy.2019.01.128.

Lu, Y., Stegman, A., Cai, Y., 2013. Emissions intensity targeting: From China's 12th Five Year Plan to its Copenhagen commitment. Energy Policy 61, 1164–1177. URL: http://www.sciencedirect.com/science/article/pii/S030142151300582X, doi:10.1016/j.enpol.2013.06.075.

Luderer, G., Leimbach, M., Bauer, N., Kriegler, E., Baumstark, L., Bertram, C., Giannousakis, A., Hilaire, J., Klein, D., Levesque, A., Mouratiadou, I., Pehl, M., Pietzcker, R., Piontek, F., Roming, N., Schultes, A., Schwanitz, V.J., Strefler, J., 2015. Description of the REMIND Model (Version 1.6). SSRN Scholarly Paper ID 2697070. Social Science Research Network. Rochester, NY. URL: https://papers.ssrn.com/abstract=2697070.

Luderer, G., Vrontisi, Z., Bertram, C., Edelenbosch, O.Y., Pietzcker, R.C., Rogelj, J., Boer, H.S.D., Drouet, L., Emmerling, J., Fricko, O., Fujimori, S., Havlík, P., Iyer, G., Keramidas, K., Kitous, A., Pehl, M., Krey, V., Riahi, K., Saveyn, B., Tavoni, M., Vuuren, D.P.V., Kriegler, E., 2018. Residual fossil CO 2 emissions in 1.5–2 °C pathways. Nature Climate Change 8, 626. URL: https://www.nature.com/articles/s41558-018-0198-6, doi:10.1038/s41558-018-0198-6.

Marangoni, G., Tavoni, M., Bosetti, V., Borgonovo, E., Capros, P., Fricko, O., Gernaat, D.E.H.J., Guivarch, C., Havlik, P., Huppmann, D., Johnson, N., Karkatsoulis, P., Keppo, I., Krey, V., Ó Broin, E., Price, J., van Vuuren, D.P., 2017. Sensitivity of projected long-term CO2 emissions across the Shared Socioeconomic Pathways. Nature Climate Change advance online publication. URL: http://www.nature.com/nclimate/journal/vaop/ncurrent/full/nclimate3199.html, doi:10.1038/nclimate3199. 00000.

Marschinski, R., Edenhofer, O., 2010. Revisiting the case for intensity targets: Better incentives and less uncertainty for developing countries. Energy Policy 38, 5048–5058. URL: http://www.sciencedirect.com/science/article/pii/S0301421510003071, doi:10.1016/j.enpol.2010.04.033. 12.

Mi, Z., Meng, J., Guan, D., Shan, Y., Song, M., Wei, Y.M., Liu, Z., Hubacek, K., 2017a. Chinese CO 2 emission flows have reversed since the global financial crisis. Nature Communications 8, 1–10. URL: https://www.nature.com/articles/s41467-017-01820-w, doi:10.1038/s41467-017-01820-w. number: 1 Publisher: Nature Publishing Group.

Mi, Z., Wei, Y.M., Wang, B., Meng, J., Liu, Z., Shan, Y., Liu, J., Guan, D., 2017b. Socioeconomic impact assessment of China's CO2 emissions peak prior to 2030. Journal of Cleaner Production 142, 2227–2236. URL: http://www.sciencedirect.com/science/article/pii/S0959652616318935, doi:10.1016/j.jclepro.2016.11.055.

Morgan, M.G., 2018. Uncertainty in long-run forecasts of quantities such as per capita gross domestic product. Proceedings of the National Academy of Sciences 115, 5314–5316. URL: http://www.pnas.org/content/115/21/5314, doi:10.1073/pnas.1805767115.

Mouratiadou, I., Luderer, G., Bauer, N., Kriegler, E., 2016. Emissions and their drivers: sensitivity to economic growth and fossil fuel availability across world regions. Climatic Change 136, 23–37. URL: http://link.springer.com/10.1007/s10584-015-1368-4, doi:10.1007/s10584-015-1368-4.

Neuenkirch, M., Neumeier, F., 2015. The impact of UN and US economic sanctions on GDP growth. European Journal of Political Economy 40, 110–125. URL: http://www.sciencedirect.com/science/article/pii/S0176268015000816, doi:10.1016/j.ejpoleco.2015.09.001.

OECD, O., 2018. Domestic product - GDP long-term forecast - OECD Data. URL: http://data.oecd.org/gdp/gdp-long-term-forecast.htm.

O'Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., Vuuren, D.P.v., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Climatic Change 122, 387–400. URL: http://link.springer.com/article/10.1007/s10584-013-0905-2, doi:10.1007/s10584-013-0905-2.

Pahle, M., Burtraw, D., Flachsland, C., Kelsey, N., Biber, E., Meckling, J., Edenhofer, O., Zysman, J., 2018. Sequencing to ratchet up climate policy stringency. Nature Climate Change 8, 861–867. URL: https://www.nature.com/articles/s41558-018-0287-6, doi:10.1038/s41558-018-0287-6.

Pizer, W.A., 2005. The case for intensity targets. Climate Policy 5, 455–462. URL: http://www.tandfonline.com/doi/abs/10.1080/14693062.2005.9685570, doi:10.1080/14693062.2005.9685570. 49.

Quirion, P., 2005. Does uncertainty justify intensity emission caps? Resource and Energy Economics 27, 343–353. URL: http://www.sciencedirect.com/science/article/pii/S0928765505000382, doi:10.1016/j.reseneeco.2005.05.002. 23.

Roelfsema, M., van Soest, H.L., Harmsen, M., van Vuuren, D.P., Bertram, C., den Elzen, M., Höhne, N., Iacobuta, G., Krey, V., Kriegler, E., Luderer, G., Riahi, K., Ueckerdt, F., Després, J., Drouet, L., Emmerling, J., Frank, S., Fricko, O., Gidden, M., Humpenöder, F., Huppmann, D., Fujimori, S., Fragkiadakis, K., Gi, K., Keramidas, K., Köberle, A.C., Aleluia Reis, L., Rochedo, P., Schaeffer, R., Oshiro, K., Vrontisi, Z., Chen, W., Iyer, G.C., Edmonds, J., Kannavou, M., Jiang, K., Mathur, R., Safonov, G., Vishwanathan, S.S., 2020. Taking stock of national climate policies to evaluate implementation of the Paris Agreement. Nature Communications 11, 1–12. URL: https://www.nature.com/articles/s41467-020-15414-6, doi:10.1038/s41467-020-15414-6. number: 1 Publisher: Nature Publishing Group.

Stern, N., 2007. The Economics of Climate Change by Nicholas Stern. URL: /core/books/economics-of-climate-change/A1E0BBF2F0ED8E2E4142A9C878052204, doi:10.1017/CBO9780511817434.

Sue Wing, I., Ellerman, A.D., Song, J., 2006. Absolute vs. Intensity Limits for CO2 Emission Control: Performance Under Uncertainty. Technical Report. MIT Joint Program on the Science and Policy of Global Change. URL: http://dspace.mit.edu/handle/1721.1/31204. 9.

UNEP, 2017. The Emissions Gap Report 2017: A UN Environment Synthesis Report. URL: https://wedocs.unep.org/handle/20.500.11822/22070.

UNFCCC, 2015. Paris Agreement. UNFCCC URL: https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement.

Vuuren, D.v., Elzen, M.d., Berk, M., Moor, A.d., 2002. An evaluation of the level of ambition and implications of the Bush Climate Change Initiative. Climate Policy 2, 293–301. URL: https://doi.org/10.3763/cpol.2002.0235, doi:10.3763/cpol.2002.0235.

Wang, H., Chen, W., Bertram, C., Malik, A., Kriegler, E., Luderer, G., Després, J., Jiang, K., Krey, V., 2019a. Early transformation of the Chinese power sector to avoid additional coal lock-in. Environmental Research Letters URL: http://iopscience.iop.org/10.1088/1748-9326/ab5d99, doi:10.1088/1748-9326/ab5d99.

Wang, H., Chen, W., Zhang, H., Li, N., 2019b. Modeling of power sector decarbonization in China: comparisons of early and delayed mitigation towards 2-degree target. Climatic Change URL: https://doi.org/10.1007/s10584-019-02485-8, doi:10.1007/s10584-019-02485-8.

Wang, J., Wu, Y., Zhao, Y., He, S., Dong, Z., Bo, W., 2019c. The population structural transition effect on rising per capita CO2 emissions: evidence from China. Climate Policy 19, 1250–1269. URL: https://doi.org/10.1080/14693062.2019.1664381, doi:10.1080/14693062.2019.1664381.

Wang, Q., 2014. China should aim for a total cap on emissions. Nature News 512, 115. URL: http://www.nature.com/news/china-should-aim-for-a-total-cap-on-emissions-1.15705, doi:10.1038/512115a.

Webster, M., Sue Wing, I., Jakobovits, L., 2010. Second-best instruments for near-term climate policy: Intensity targets vs. the safety valve. Journal of Environmental Economics and Management 59, 250–259. URL: http://www.sciencedirect.com/science/article/pii/S0095069610000240, doi:10.1016/j.jeem.2010.01.002. 16.

Zheng, J., Mi, Z., Coffman, D., Milcheva, S., Shan, Y., Guan, D., Wang, S., 2019. Regional development and carbon emissions in China. Energy Economics 81, 25–36. URL: http://www.sciencedirect.com/science/article/pii/S0140988319300829, doi:10.1016/j.eneco.2019.03.003.

Zhu, B., Jiang, M., Wang, K., Chevallier, J., Wang, P., Wei, Y.M., 2018. On the road to China's 2020 carbon intensity target from the perspective of "double control". Energy Policy 119, 377–387. URL: http://www.sciencedirect.com/science/article/pii/S0301421518302416, doi:10.1016/j.enpol.2018.04.025.

Zhu, B., Wang, K., Chevallier, J., Wang, P., Wei, Y.M., 2015. Can China achieve its carbon intensity target by 2020 while sustaining economic growth? Ecological Economics 119, 209–216. URL: http://www.sciencedirect.com/science/article/pii/S0921800915003638, doi:10.1016/j.ecolecon.2015.08.015.

3

Uncertainty in Techno-Economic Parameters *

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How uncertainty in technology costs and carbon dioxide removal availability affect climate mitigation pathways

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Limiting global warming to “well below 2°C” as stated in the Paris Agreement requires ambitious emissions reductions from all sectors. Rapid technology cost declines in the energy sector are changing energy investment and emissions, even with the weak climate policies currently in place. We assess how energy supply costs and carbon dioxide removal (CDR) availability affect mitigation by performing a sensitivity analysis with the energy-economy-climate model REMIND. We use new scenarios with carbon price paths that aim to reduce the frequently seen temperature overshoot. Further, we measure the sensitivities of mitigation indicators to the costs of technologies across economic sectors. We assess the sensitivity to nine techno-economic parameters: the costs of wind, solar, biomass, gas, coal, oil, nuclear, and electric/hydrogen vehicles, as well as the injection rate of Carbon Capture and Storage (CCS). While technology costs play a role in shaping optimal pathways, we find that transport sector costs affect the economics of deep decarbonization, whereas costs of renewables are more important for scenarios under weak climate policies. This further highlights the value of renewable energy deployment as a no-regrets option in climate policy. In terms of the sensitivity of model outputs, economic indicators become more sensitive to costs than emissions, with increasing policy stringency.

1. Introduction

The energy sector accounts for the largest share of greenhouse gas (GHG) emissions [1] and holds the greatest decarbonization potential [2]. Thus, investments in energy transformation technologies are key factors shaping climate mitigation pathways [3–6]. Previous studies have shown that the uncertainty associated with the costs of energy technologies constitutes an important component of the overall uncertainty present in mitigation pathways [7–11].

Energy investment costs have changed drastically over time and vary considerably across space [12]. Solar and onshore wind have levelized costs of electricity (LCOE) that are in some regions lower than the long-run-marginal-cost (LRMC) of standing coal capacity, but analysts suggest a strong policy signal (in the form of carbon price or efficiency standard) is still needed for a fast decarbonization of the power sector [13–18]. At the same time, the decarbonization of the transportation sector is proceeding [19] and depends on the cost of electric and fuel-cell vehicles [20–22], as well as oil prices [23], and policies [24].

Given recent changes, what are the differences in computing global mitigation pathways using 2015 technology cost projections versus 2019 costs? How are CDR[1] demands and individual sectors affected? What is the relative importance of the costs of technologies when compared with each other? and which mitigation indicators are affected the most by these costs? In an approach similar to Bosetti et al. [25]; we tackle these uncertainties by performing a sensitivity analysis of mitigation indicators on energy technology costs, under various levels of climate policy ambition. We assess the sensitivity of nine techno-economic parameters:

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[1] Carbon Dioxide Removal.

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Table 1
Number of model runs—per policy and CDR availability scenario—needed for the extended one-factor-at-a-time method used here, and scenario description. Explanation of numerical values: 3 refers to the reference cases (all factors at reference value/all factors at high/all factors at low), 9 to the number of factors (BIO, CCS, COAL, etc.), and 4 to the sensitivity cases (factor value at high/low/others-high/others-low). Temperature increase is global mean surface-air temperature increase compared to the mean of 1850–1900 in 2100, CO2 budgets are given in the period 2011–2100.

	with CDR	without CDR	Description
No-policy baseline	3+9x4	3+9x4	Counterfactual scenario without climate policies
NDC	3+9x4	3+9x4	Nationally Determined Contributions continued without increased ambition
B1300	3+9x4	3+9x4	67% prob. of 2°C; 1300 Gt CO2 in 2011–2100
B1100	3+9x4	3+9x4	"well below" 2°C; 1100 Gt CO2 in 2011–2100
B900	3+9x4	3+9x4	67% prob. of 1.5°C; 900 Gt CO2 in 2011–2100

renewable energy (wind, solar photovoltaics and concentrated solar power (CSP)) technology costs, nuclear power plant costs, cost curves for fossil fuel extraction (gas, coal, oil), biomass supply costs, as well as rates of injecting carbon dioxide (CO2) into the ground (CCS[2]). The CO2 injection rate crucially determines the mitigation potential of BECCS (bioenergy with CCS), an important CDR technology. We also consider costs of electric and hydrogen-fueled vehicles, as alternatives to oil in the transport sector. The techno-economic parameters are chosen so as to cover the entire energy supply, with two important additions: one from the energy demand side (vehicle costs), and the CO2 injection rate. We further contrast scenarios including large-scale CDR with scenarios where CDR—other than reforestation and afforestation—is not allowed. Apart from being a useful tool for answering the above questions, sensitivity analysis is good scientific practice for enhancing transparency and the credibility of model results for informing societal decisions [26,27].

The remainder of the paper is structured as follows. In the next section, we describe the scenarios and methods used here: the climate policy scenarios, the technology cost ranges, and the sensitivity analysis method. We then present the results starting with the insights gained from the effect that technology costs have on global outcomes across sectors, followed by a ranking of important mitigation indicators with respect to their relative sensitivity to technology costs. Section 5 summarizes and concludes. We compute all scenarios with the large-scale and technologically detailed energy-economy model REMIND. See Appendix A.1 for a detailed description.

2. Scenarios and methods

2.1. Climate policy scenarios

Table 1 shows the scenarios considered, which feature an extensive coverage of climate policy ambition, and use SSP2[3] socio-economic assumptions. The scenarios range from a no-policy baseline (BASE) to a continuation of the currently announced Paris pledges (NDC) and three different scenarios (B900, B1100, B1300) assuming global CO2 emissions are constrained by a budget of 900, 1100 and 1300 Gt CO2 in the time period 2011-peak year, respectively. With "peak-year" we refer to the year where global mean temperature peaks.

Typical budget scenarios usually feature carbon prices[4] increasing exponentially until the end of the century, and tend to show increased demand for CDR and an overshoot in temperature. Here, we use newly developed scenarios [28] with carbon prices increasing steeply until net carbon emissions become zero (this point corresponds also to roughly the peak temperature point), and increase slowly afterwards (see Fig. A.8 of the Appendix). This carbon price trajectory leads to a moderate need for CDR, a reduced overshoot in the global mean temperature, and is more in line with the interpretation of the Paris climate targets as not-to-exceed limits [29].

To isolate the effect of energy technology costs from CDR availability, we consider scenarios with and without additional CDR technologies[5] (direct air capture and BECCS). The full ensemble of approximately 400 scenarios is found in the Appendix. Fig. 1 visualizes the technology cost uncertainty by showing CO2 emissions (by sector and total), carbon prices, and consumption losses for the baseline, NDC, and B1100 policy scenarios. For each indicator, policy, and CDR availability scenario, a different spread is observed in the computed values. Quantifying and understanding this uncertainty is the goal of this paper. Due to space constraints, we focus on our main scenario B1100; other scenarios are described in the Appendix.

2.2. Technology cost ranges

The nine (groups of) technologies with uncertain costs (or potential) are shown in Table 2, while an overview of the ranges considered in the sensitivity analysis is given in Fig. A.9, expressed in terms of low, medium, and high levels for each. REMIND computes endogenous resource market prices, thus for the sensitivity of the costs of fossil fuels (oil, coal, gas) we choose the extraction costs according to the SSP scenario variation: SSP1, SSP2, and SSP5 [30], delivering the low, medium, and high cases, respectively. The SSP scenarios feature extraction cost curves for each of REMIND's world regions, the average of which is shown in Fig. A.9. For the variation of the remaining energy conversion technologies we use capital costs, whereas for CCS we use CO2 injection rates. Capital cost uncertainty is important also because of a potential rise of interest rates in the future. Our cost ranges for renewables are derived from observed investment cost ranges (high, reference, and low; source: LCOE ranges from IRENA [31]. Nuclear power plant costs are varied by a range derived from observed typical cost overruns during construction. To visualize the resulting ranges we plot the turnkey costs for wind, solar photovoltaics, CSP, nuclear, as they are used in REMIND. We vary simultaneously costs of battery-electric and full-cell vehicles ("ELH2" will be used throughout the paper to refer to the pair) by observed purchase costs (5th and 95th percentile of the cost of a medium size vehicle, Cox et al. [32], and the CCS injection rate according to the following values: 0,5% (reference, yielding roughly 60 Mt CO2 per day), 0,1% (low injection rate, corresponding to the "high" case in the sensitivity analysis, as in "low availability",

[2] Carbon Capture & Storage.
[3] Shared socio-economic pathways [50].
[4] climate policy in all our scenarios is enforced via a global, uniform, lump-sum carbon price, covering also CH4 and N2O emissions. These are also reduced in policy scenarios, but by prescribed paths.
[5] CDR from exogenous reforestation and afforestation scenarios is always allowed.

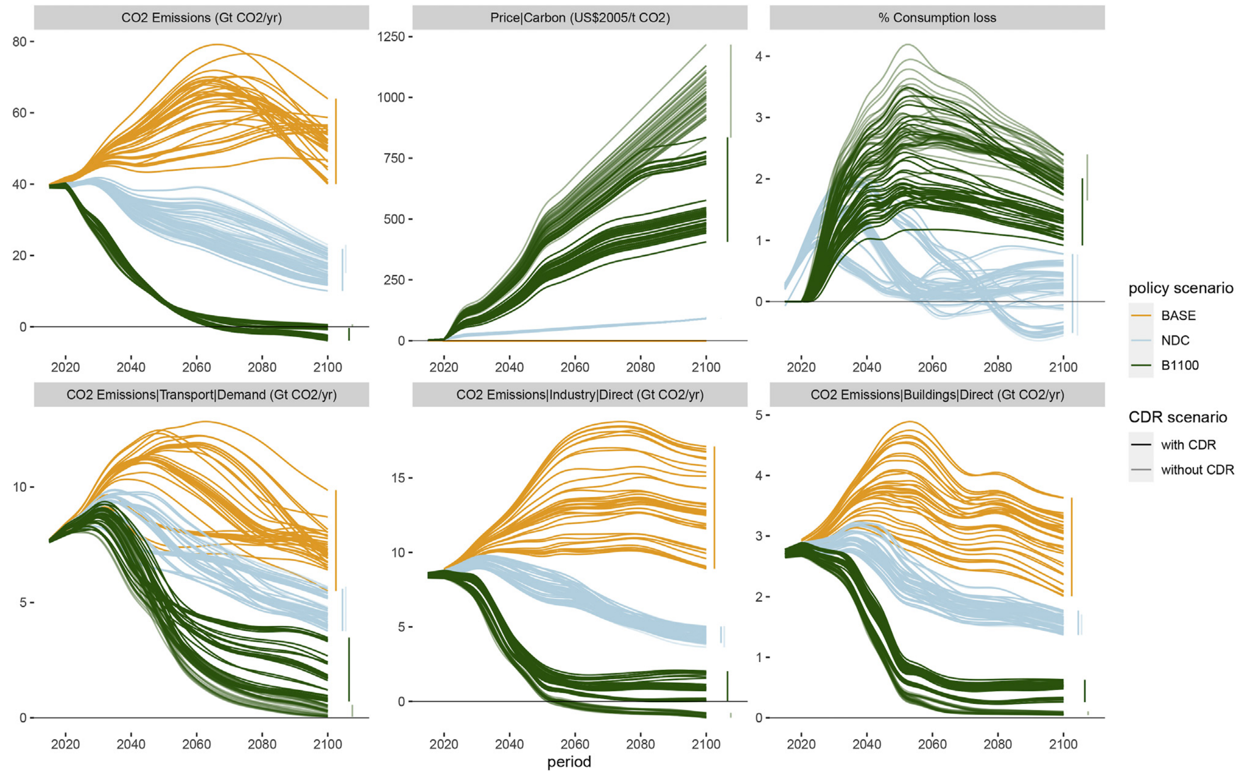

Fig. 1. Impact of technology uncertainty on mitigation. The ensemble of scenarios for the no-policy baseline, NDC continuation, and B1100 scenarios, see Table 1. Indicators shown are emissions (total and by sector), policy costs, and carbon price. Throughout the paper, the unit chosen for the net present value of the carbon price is US%2005, same holds for the rest of the monetary values, e.g. costs (US$2005 is the internal currency of the REMIND model). Technology costs are the source of uncertainty of all policy scenarios. Vertical lines on the right show the uncertainty range. Sectors (lower row of indicators) feature similar uncertainty range, but transport has a stronger variation in the stringent policy case (B1100; transport is also the only sector with rising short-term emissions). The NDC scenarios clearly fall short of adequate emissions reductions for reaching ambitious climate goals. Uncertainty in economics increases with policy stringency, while uncertainty in emissions decreases. CDR availability increases the uncertainty range (vertical lines), giving more flexibility to the system. The same graph including also the B900 and B1300 scenarios is found in the Appendix.

Table 2
Technologies with uncertain costs (or potential) considered in the present study. REMIND features specific costs per region, the values shown here are the global average. The price (and usage) paths resulting from the given input parameter uncertainty ranges are plotted in Fig. A.9

Technology	Short name	Techno-economic parameter	Ranges (2050) Low	Medium	High
Wind power converters	WIND	Capital cost (US$2005/kW)	480	830	1290
Utility scale solar PV & CSP	SOLAR	Capital cost (US$2005/kW)	180/1500	230/2350	420/3300
Nuclear power plants	NUCLEAR	Capital cost (US$2005/kW)	2700	6000	8750
Electric & fuel-cell H2 vehicles	ELH2	Purchase cost (US$2005/veh)	7700/11500	12500/20000	17700/27000
Carbon Capture & Storage	CCS	CO2 injection rate (Mt CO2/day)	12	60	(unconstrained)
Biomass	BIO	Extraction cost (US$2005/GJ)	−50%	2	+50%
Coal	COAL	Extraction cost (US$2005/GJ)	1	1.57	1.9
Gas	GAS	Extraction cost (US$2005/GJ)	2.41	3	4.06
Oil	OIL	Extraction cost (US$2005/GJ)	4.3	7.87	11

i.e. high cost; for compatibility with the other varied inputs), 100% (unconstrained injection rate, corresponds to the "low" case in the sensitivity analysis). Finally, biomass extraction costs (also highly uncertain like the CCS injection rate) are varied by 50% higher and lower compared to the reference SSP2 value.

2.2.1. Modelling of energy technology costs

The costs of energy technologies in REMIND, which are balanced in the macro-economic budget equation, consist of those arising from the extraction of energy resources and the investment in—and use of—energy conversion technologies.

First, the costs associated with the extraction of coal, oil, gas, and uranium are represented by regional long-run marginal supply cost curves which relate cumulative resource extraction to marginal costs [30,33,34]. These costs increase with cumulative extraction reflecting the transition from low-costs (e.g. conventional oil) to high-costs mines and deposits (e.g. offshore oil, tight oil, oil shale) [33,35,36]. In addition, the production of fossil fuels is subject to adjustment costs that are represented by quadratic curves and account for the costs increase stemming from short-term changes in production [37]. Trade costs are added to the overall production fuel costs [37]. Bioenergy costs are also modelled by supply cost curves that capture the time, scale, and region dependent change of bioenergy production costs, as well as path dependencies resulting

Table 3
Characteristics of mitigation indicators (model outputs).

Group	Indicator	By Sector	Year	Aggregated
1 Economics	Carbon tax	No	2100	No
	Climate policy costs	No	2010–2100	Yes
2 Depth	CO2 emissions	Yes	2030–2050 mean	No
	Electricity share of final energy	Yes	2030–2050 mean	No
	Fossil carbon intensity of fuels	Yes	2030–2050 mean	No
3 CDR and YCN	Cumulated CDR	No	2020–2100	Yes
	Year of carbon neutrality	No	–	No

from past land conversions and induced technological changes in the land-use sector [38].

Secondly, each energy conversion technology is characterised by investment costs, operation and maintenance costs, and fuel costs [39]. Investment costs are modelled as turnkey costs and are regionally differentiated. These are computed by adding financing costs that occur over the construction time of technologies to specific overnight capital costs with a view to capture differences in the cost of capital across technologies and regions. Investment costs remain relatively constant for most technologies (e.g. coal power plant) and decrease for some relatively new technologies (e.g. wind and solar photovoltaics, electric/hydrogen vehicles), due to rapid innovation and technological change. Technological change is modelled via learning curves that relate cumulative capacity installation to marginal costs. Operation and maintenance costs are divided into fixed yearly operating and maintenance costs which are estimated as a fraction of investment costs and variable operating costs which scale with energy output. Finally, fuel costs are those arising from the energy resource production described in the previous paragraph.

2.3. Sensitivity analysis (method description)

Here, the sensitivity analysis of techno-economic parameters (technology and extraction costs, injection rate, purchase costs of electric/hydrogen vehicles) using the energy-economy-climate model REMIND will be presented. We will refer to the techno-economic parameters as factors (i.e. model inputs in sensitivity analysis jargon). Due to the model size (60+ energy technologies, 12 world regions, 19 time-steps) an extended one-factor-at-a-time method featuring efficient sampling is used here, same as in Marangoni et al. [40]. “Extended” refers to the ability of the method to compute also the factor interaction effect [41], which is computed as follows: each factor is changed to its high (or low) value while all other factors are kept at their reference value, and, additionally, each factor is fixed at its reference value while all other factors are moved to their high (or low) values. The former gives the first-order (or direct) effect of a factor, while the latter—with a change in sign—gives the total effect of the factor in question.

3. The effect of technology costs on mitigation indicators

We present the results in two parts. First, to quantify the sources of uncertainty we show the individual effect of technology costs on selected mitigation indicators. Second, to answer the question about which mitigation indicators are affected the most by technology costs, we compute aggregate measures that summarize the individual effects. We then compare the sensitivities (sensitivity indices) of the indicators. We separate the mitigation indicators (model outputs) into three thematic groups, to provide a better structure and increase the readability of the results. The first group relates to the economics of decarbonization, the second contains indicators describing the depth of decarbonization by mid-century, and the third contains CDR demand and the year of carbon neutrality (YCN). See Table 3 for detail.

3.1. Economic indicators

Results for the first indicator group are shown in Fig. 2, which presents four modified tornado-diagrams, similar to the ones commonly used in sensitivity analyses. The figure shows the indicator reference value (shown separately at the top in grey bars) as well as the magnitude and direction of change from reference to low/high for each factor. It thus illustrates how much each factor affects each indicator and allows comparisons of the relative importance of each. The corresponding graphs for the B900 and B1300 scenarios are found in Fig. A.11. In tornado-diagrams,factors are typically sorted with the most influential at the top, the resulting shape is what gives them this name. Here, we modify the diagram by sorting the factors in thematic color-coded clusters: renewables (green), nuclear (purple), low-carbon mobility (light blue), biomass and CCS (pink), and fossil (brown).

Climate policy costs[6] increase by 20% when low-carbon mobility (electric vehicles and hydrogen-powered fuel-cell vehicles, ELH2) is more expensive, and the CCS injection rate is low (red bars). This is the largest increase, followed by an 8% increase in policy costs if oil extraction were lower cost. The highest cost decrease (9%) comes also from ELH2 being cheaper, followed by wind and biomass/coal (8%). Similar dynamics occur in the no-CDR case, seen in the bottom left panel of Fig. 2. Biomass is an important factor also in the absence of CDR. Carbon prices react in a much more sensitive way to CCS availability than policy costs, but the effect of ELH2 and oil remains significant also here, and becomes even more pronounced in the no-CDR case. The other three policy scenarios (and their no-CDR alternatives) show the same behavior in policy costs and carbon prices (in the Appendix). Overall, transport-related costs (ELH2 and oil) alongside biomass and CCS have the largest impact on the economic indicators.

3.2. Depth of decarbonization

Fig. 3a shows the reference values for the second group of indicators (depth of decarbonization), and adds the sectoral dimension. The indicators here describe the average progress made in decarbonization in the period 2030–2050. Sectoral emissions from buildings, industry, and transportation exclude indirect emissions from upstream, e.g. electricity. Fig. 3(b–f) are modified tornado-diagrams showing sensitivities to technology costs and CCS availability. In the total values (Fig. 3b), ELH2 and CCS have the biggest effect on emissions, followed by an emissions decrease at low costs for wind and oil. The strong effect the costs of renewables have on the electricity share of final energy is comparable to the effect of

[6] Net present value of consumption losses in the period 2011–2100, relative to the no-policy baseline.

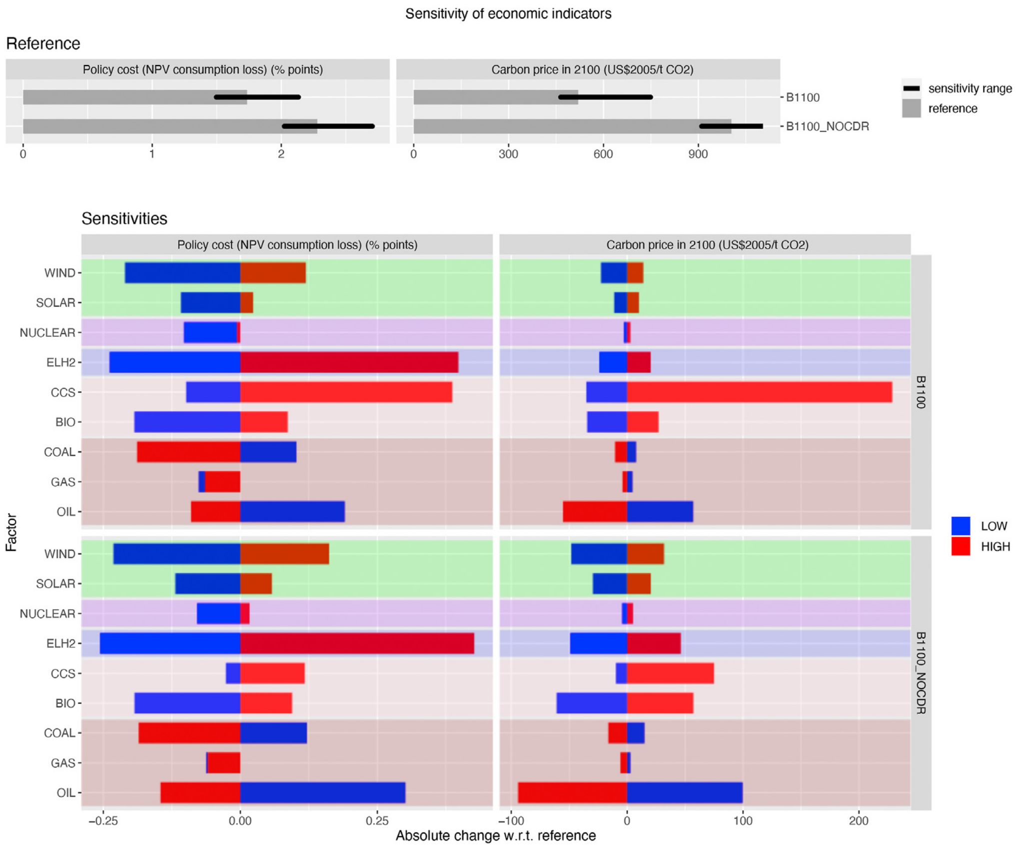

Fig. 2. Modified tornado-diagrams: Economic indicators. The Sensitivities panel shows absolute change (x axis) in mitigation indicators caused by a one-factor-at-a-time variation of technology costs (y axis). Blue bars correspond to low cost, red bars to high cost (for the CCS injection rate, the only technology where a physical property rather than costs is varied, the colors are used to reflect how "accessible" the technology is—thus red is low rate and blue is high). Reference values (equal across factors) are shown with grey horizontal bars at the top, black lines show the sensitivity ranges. Example on how the information on the diagrams is interpreted: "cheap oil and expensive ELH2 lead to increased policy costs in a B1100 scenario", etc. The policy costs are described as net present value consumption losses relative to the baseline, aggregated over the period 2010–2100 and discounted at 5%. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

ELH2. In contrast the impact of renewables on fossil carbon intensity is lower than those of ELH2 and oil.

Demand-sector contributions are shown in Fig. 3(c–e). The transport sector (e) includes the largest individual factor effects of the analysis, ELH2 and oil. Electricity supply (f) shows the highest overall sensitivity, combining indirect effects from downstream changes in demand (oil, ELH2, CCS) and the direct influence of technology costs (solar, wind, and nuclear). Conversely, fossil resource prices other than oil show a limited influence on power sector decarbonization, shown by the fossil carbon intensity of fuels.

3.3. CDR and year of carbon neutrality

Overall, CDR adds flexibility to the system, which leads to a stronger effect of energy technology costs on mitigation than in the cases without CDR. For example, see the increase in the uncertainty ranges of Fig. 1, as well as the differences between Fig. 3 and A.12. Fig. 4 shows the impact of costs on CDR use. The CCS injection rate has the highest impact, but in the case of unconstrained injection (blue bar) the effect is very limited compared to low injection, where CDR is reduced by more than 50%. This shows that the reference value for the injection rate limit leads to CDR use that is close to the economic optimum for the model—constraining injection further has a large effect, but relaxing it does relatively little. Another 12% variation comes from the uncertainty in oil prices.

The year of carbon neutrality is also largely unaffected by the variation of the factors, except for CCS and ELH2. Also here an unconstrained injection rate does not have an impact, compared to a strong shift of more than 10 years if the CCS injection rate is low. In the case of ELH2, lower purchase costs would lead to a decrease in emissions in the short-term that would then need to be compensated less by CDR later on, shifting the YCN to the right compared to the reference.

3.4. Relative sensitivities of indicators

There are several approaches to summarizing sensitivity analysis results. In most cases the so-called sensitivity indices are computed, describing the impact of model inputs on model outputs. We apply two different metrics for the calculation of the sensitivity indices. The first one is described by the direct effect a factor has on the *variance* of a certain output and is called first order Sobol' index [42]:$S_i = \frac{V_{X_i}(\mathbf{E}_{\mathbf{X}_{\sim i}}(Y|X_i))}{V(Y)}$, where i: factor, $\mathbf{X}$: vector of factors, $\mathbf{E}$: expected value operator, Y: indicator, and V: indicator variance.

The second metric is described by the total effect a factor has on the *percent change* of an indicator from its reference value; total in this case refers to the sum of the direct effect (like above) *plus* the interaction effect of the factor in question with the rest of the

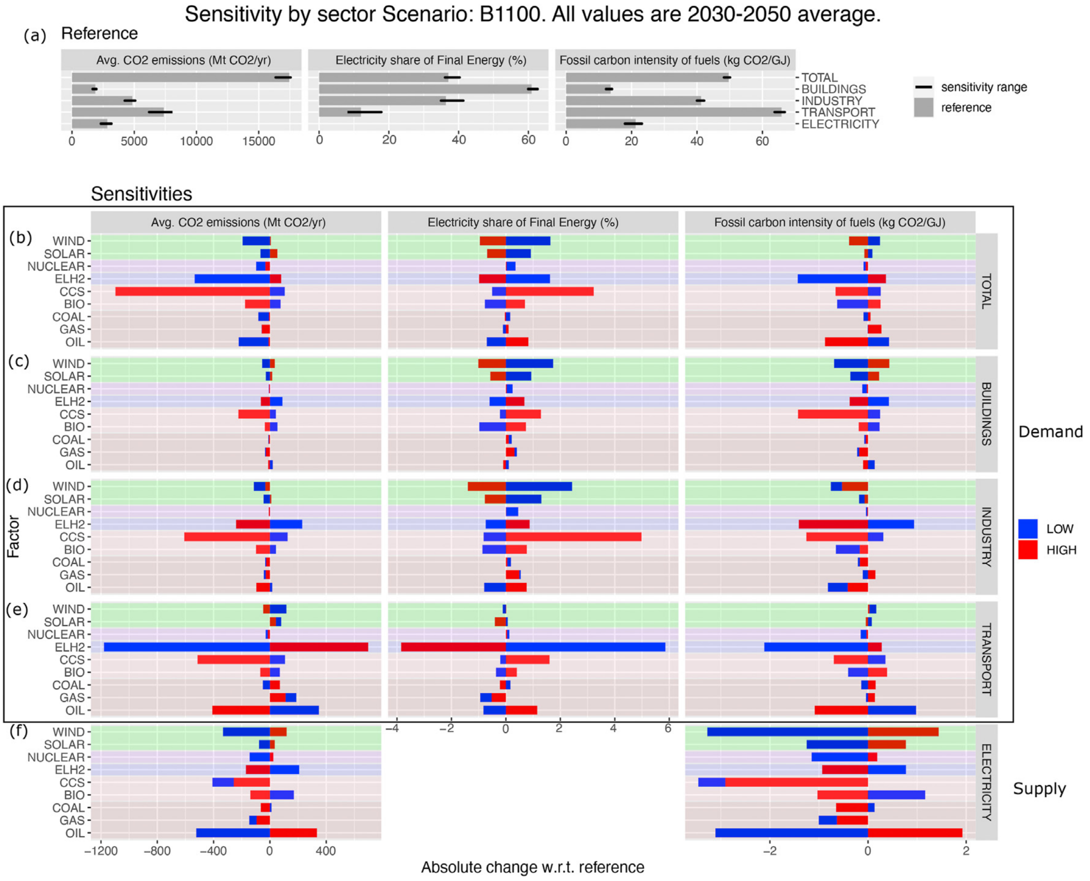

Fig. 3. Modified tornado-diagrams with sectoral detail. Absolute change (x axis) in the indicators describing the depth of decarbonization caused by one-factor-at-a-time variation of technology costs (y axis). Red bars correspond to high cost, blue bars to low. Reference values (equal across factors) are shown with grey horizontal bars at the top, black lines show the sensitivity ranges. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

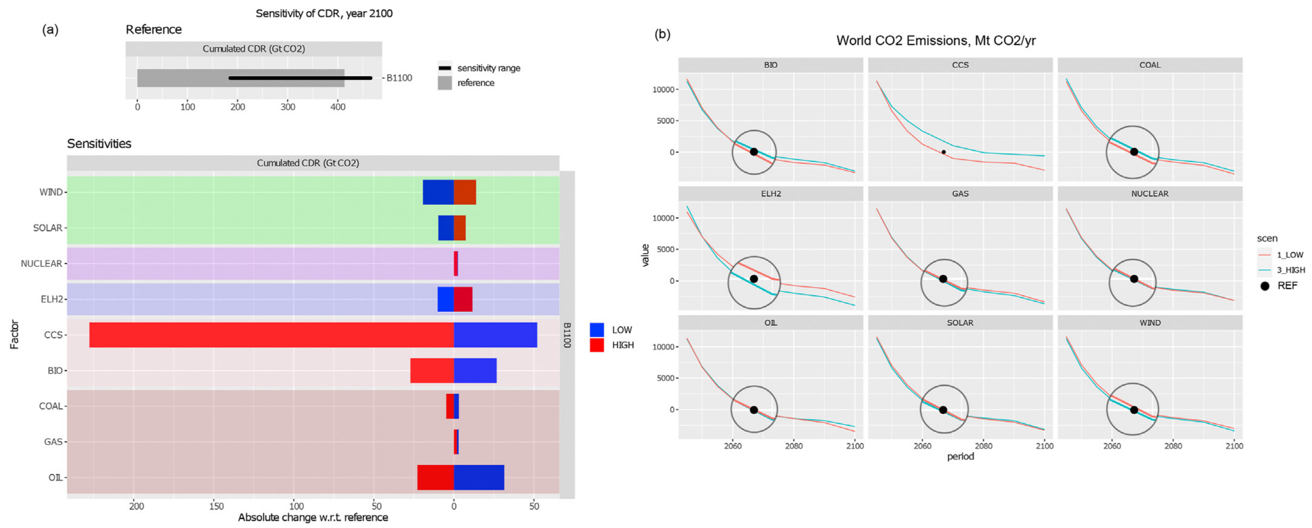

Fig. 4. CDR and year of carbon neutrality Impact of technology cost uncertainty a) on the CDR demand and b) on the shift in the year of carbon neutrality, YCN. The reference YCN is denoted by a black dot on the graph.

factors. The percent change is given by the following formula.

$$\%change = \sum_i 100 \cdot \left(\frac{|Y_{H,i} - Y_R|}{|Y_{H,i}| + |Y_R|} + \frac{|Y_{L,i} - Y_R|}{|Y_{L,i}| + |Y_R|} \right),$$ where i: factor, H: high, R: reference, L: low, and Y: indicator value.whereas the interaction effect is captured by the method described by Marangoni et al. [40];

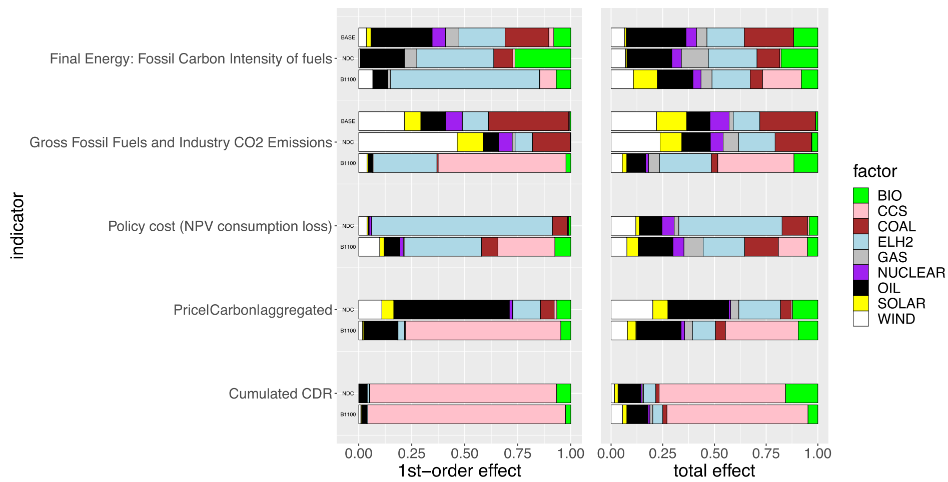

Fig. 5. Sensitivity indices Left: Sobol' first order (direct) indices describe the contribution (share) of each factor (model input) to the variance of the model outputs. Right: The total effect describes the direct contribution of each factor to the percent change in outputs plus the effect caused by the interactions of the factor with the other factors. NPV: net present value.

consisting of running—alongside scenarios with a normal one-factor-at-a-time variation—scenarios where one factor is maintained at the reference value and all the other factors are changed to the high or low values. These findings are summarized in Fig. 5, and provide a compact overview of the detailed results given in the tornado-diagrams of sections 3.1-3.3 (expanded to include also the no-policy baseline and the NDC scenario), visualizing the dominating effect of the CCS injection rate and ELH2/oil on the indicators variance and percent change. Fig. 5 also shows that the costs of renewables reach their highest impact in the NDC case. However, the NDC scenarios clearly fall short of adequate emissions reductions for reaching ambitious climate goals, as seen also in Fig. 1.

Based on the above calculations, Fig. 6 informs decision-making

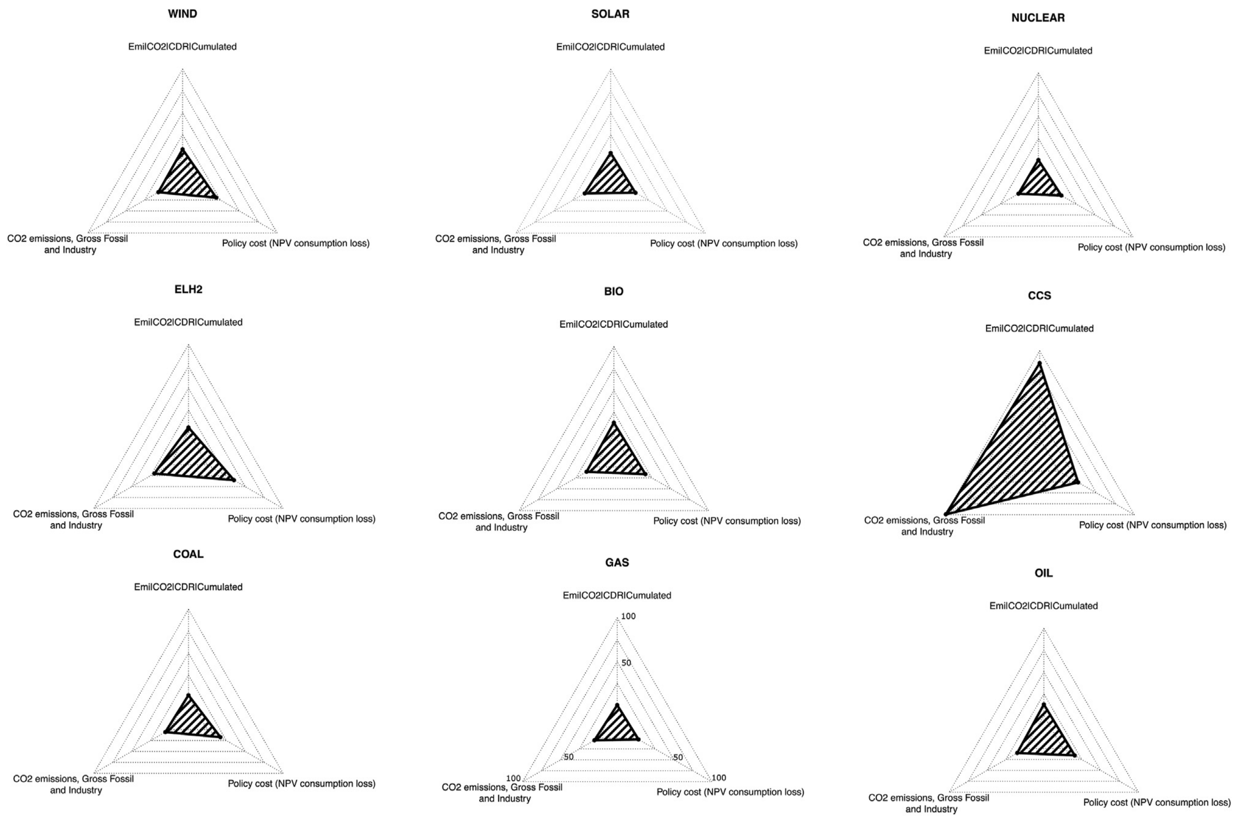

Fig. 6. Comparison of mitigation indicators by individual factor effect. The mitigation indicators shown here describe challenges (climate policy costs) and sustainability concerns related to climate change mitigation (total CDR requirements and total (gross) emissions). Scenario: B1100 with CDR, year 2100. Reference values (World total CDR/World gross emissions/Policy costs): 413 Gt CO2/5 Gt/1,74% Net present value of consumption losses 2010-2100.

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by analysing trade-offs among policy cost, mitigation, and sustainability (i.e.minimizing CDR). It assesses the effects of technology costs and CCS availability on climate policy costs, emissions, and total CDR requirements, in a B1100 scenario. Each effect is measured by computing the percent change of each indicator (compared to the reference), when going from the reference to high and ow for each factor. This way, we can visualize the type of model output that each factor is affecting the most. The transport-related factor ELH2 influences the policy costs significantly more than the other indicators, due to the constraints imposed by the low number of decarbonization options available to the sector.

3.5. Edge cases: scenarios of full- and no-flexibility

The "edge cases" of the factor values describe worlds with and without flexibility, i.e. worlds where energy technology options are either very difficult—see also the *LimTech* scenario from Kriegler et al. [4]—or very easy to reach. Here, these worlds are modelled by taking all the factors at their respective low or high cost value, at the same time. An overview of how the edge cases shape three key mitigation indicators (final energy demand, policy costs, carbon price) for the B1100 policy case is given in Fig. 7, where climate policy costs and near-term carbon prices nearly double when going from full-to no-flexibility ("all low" versus "all high"), combined with a 25% average final energy demand response. These results provide intuition about the mitigation potential of a) a wide spectrum of technology options, and b) policy instruments beyond carbon pricing. It is important to note that these edge cases give an indication of the size of the solution space only as it is seen from the viewpoint of a neutral energy/technology "planner", who does not know which options reduce emissions and which do not. This means that the edge cases do not cover the full range of mitigation outcomes from all the possible technology cost combinations. For example the case of all *mitigation* technologies being easily accessible while fossil fuels are expensive, and vice versa, are not considered here. These cases can potentially lead to even stronger variation in mitigation-related outputs as they would be tailored to explicitly favor or hinder mitigation.

4. Summary and conclusions

This sensitivity analysis of technology costs shows that the uncertainty in biomass&CCS followed by the transport-related options (ELH2 and oil) have the largest effects on both physical and economic mitigation indicators. These findings agree with results reported by Luderer et al. [43] and Kriegler et al. [4]; where the strongest variation among technologies originates from BECCS and energy intensity (transport-related). In the case of biomass&CCS, this happens because these technologies directly control the option to create net negative emissions, but in the case of low-carbon mobility and oil, the explanation is two-fold. First, increasing policy stringency requires a rapid decarbonization of the power sector, which features many complementary options—making one more expensive does not hurt very much. The buildings and industry sectors feature high electrification in the reference scenario, so only the transport sector affects carbon prices. Second, the transport sector emissions are the only ones that keep rising in the short term. These two effects make transport the price-setting sector.

The year of carbon neutrality remains largely unaffected by the variation in costs. This indicates the importance of early climate action, as even in "favorable" price scenarios, optimal emissions need to reach zero by 2065. On the other hand, the use of CDR is a more sensitive economy-wide physical mitigation indicator, mainly affected by the CCS injection limit and the dipole oil/ELH2. Furthermore, the remaining emissions of NDC scenarios with low costs of renewables raise the question of whether falling prices for renewables alone will be sufficient to reach long-term climate targets, such as the well below 2°C. Finally, the high overall influence of biomass&CCS (with uncertain potential) and transport-related technologies (difficult to decarbonize) on the indicators, highlights the need for robust and broad policy support for achieving the goals of the Paris Agreement.

The present study focuses on uncertain factors in the energy supply side, and further research shedding light onto demand-side uncertainties is needed to provide additional information for climate policy. Finally, including second-best effects, and further analysing integration constraints and market imperfections leading to the actual costs of technologies not reaching the market, would

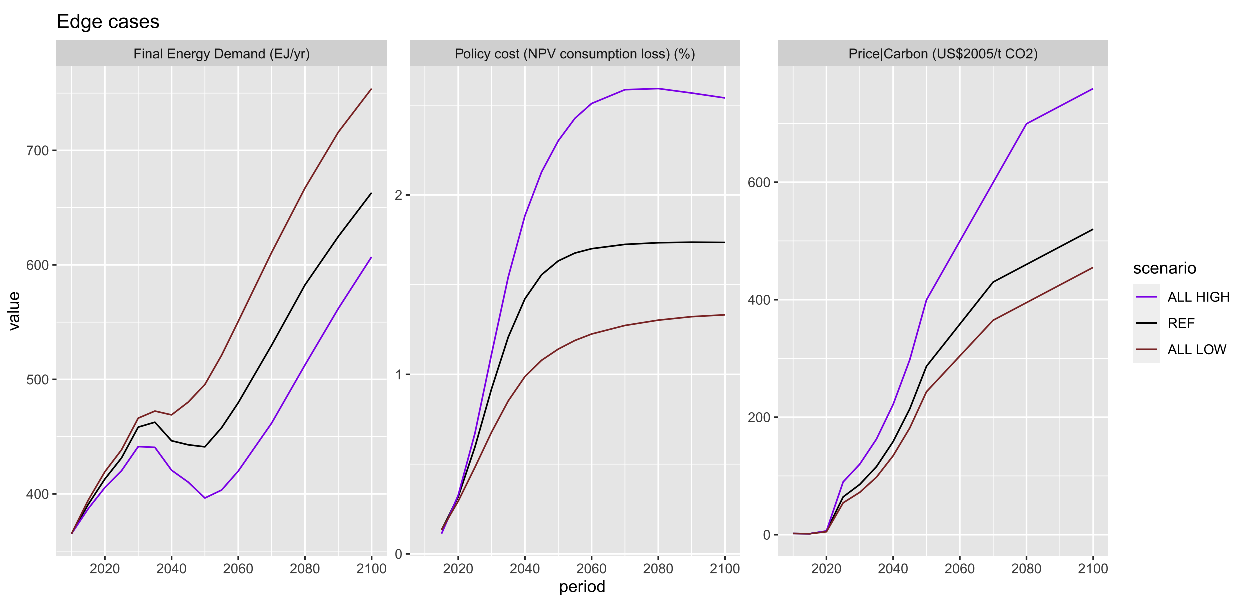

Fig. 7. Edge cases. Differences between the reference case and worlds with no- and full-flexibility (all technology costs at high and low values, respectively).

enhance the usefulness of the present findings.

Code and data availability. REMIND is open-source: https://github.com/remindmodel/remind. The version used here is REMIND v2.1.1 (https://doi.org/10.5281/zenodo.3730918).

Author contribution

Anastasis Giannousakis, designed the study, conducted the derivation of input data ranges, modeling work, post-processing, and created the figures, wrote the paper. Jérôme Hilaire, supported the post-processing, and creation of figures, supported the derivation of input data ranges, wrote the paper. Gregory F. Nemet, designed the study, supported the writing. Gunnar Luderer, supported the derivation of input data ranges, supported the writing. Robert C. Pietzcker, supported the derivation of input data ranges, supported interpreting the results and deriving conclusions, supported the writing. Renato Rodrigues, supported the derivation of input data ranges, supported the writing. Lavinia Baumstark, supported the derivation of input data ranges. Elmar Kriegler, designed the study, supported the derivation of input data ranges, All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Appendix A.1. The integrated assessment model REMIND

REMIND (REgional Model of INvestment and Development) is a multi-sector, multi-region integrated assessment model used for global and regional climate policy analysis [44]. REMIND has been used extensively in IPCC reports, e.g. IPCC [45] and IPCC [46]; and major model intercomparison projects, e.g. Kriegler et al. [4]; Pietzcker et al. [47]; Bauer et al. [48]; Luderer et al. [2]; Riahi et al. [49]. It combines a top-down Ramsey-type growth model with a bottom-up energy system model of large technological detail. In the macro-economic core of REMIND, aggregated and discounted intertemporal social welfare is maximized for a number of regions spanning the whole globe, while pathways are derived for savings and investments, factor incomes, as well as energy and material demand. The utility function of REMIND exhibits constant relative risk aversion and has a logarithmic form on consumption. Regions interact by trade in primary energy carriers, emission permits, and a composite good. The detailed representation of the energy system in each region consists of capital stocks for more than 60 technologies for energy conversion, including technologies that are able to generate negative emissions, like bioenergy combined with carbon capture and sequestration.

In REMIND, economic activity results in demand for energy services, which in turn results in GHG emissions from extraction and burning of fossil fuels in different sectors (buildings, industry, transport) and levels (primary, secondary, final, and useful energy). Mitigation scenarios analyse optimal strategies for decarbonization with the use of a carbon tax applied on the economy, resulting in a shift from fossil use to renewable energy. A full portfolio of GHG is considered (CO2, CH4, N2O, NH3, F-gases, etc.), either via emissions from energy use or via exogenous marginal abatement cost curves (e.g. land-use). Adjustment costs in energy investment and deployment account for policy realism and path dependency. REMIND usually runs in so-called cost-effectiveness mode, not internalizing potential economic damages of climate change, but rather analyzing energy technology portfolios and investment dynamics under given climate targets (carbon budgets, reduction relative to a baseline, carbon taxes, etc.). REMIND features endogenous technological learning for several energy conversion technologies (investment costs decrease with increasing installed capacity).

Appendix A.2. The effect of technology costs on the baseline, NDC, and B900/B1300 scenarios

Fig. A.11 shows the variation of the economic indicators (see Table 3) for the B900 and B1300 scenarios. We observe the same dynamics as in the B1100 scenario (see section 3.1 of the main article), with the effects of ELH2, oil and CCS becoming more pronounced as target stringency increases from B1300 to B1100 and B900. Conversely, the overall effect of technology uncertainty on emissions is reduced when going from NDC to B1100 and further to B900 (see Figs. A.14 and A.13). The sensitivity of CDR use scales with increasing policy ambition as seen on Fig. A.15.

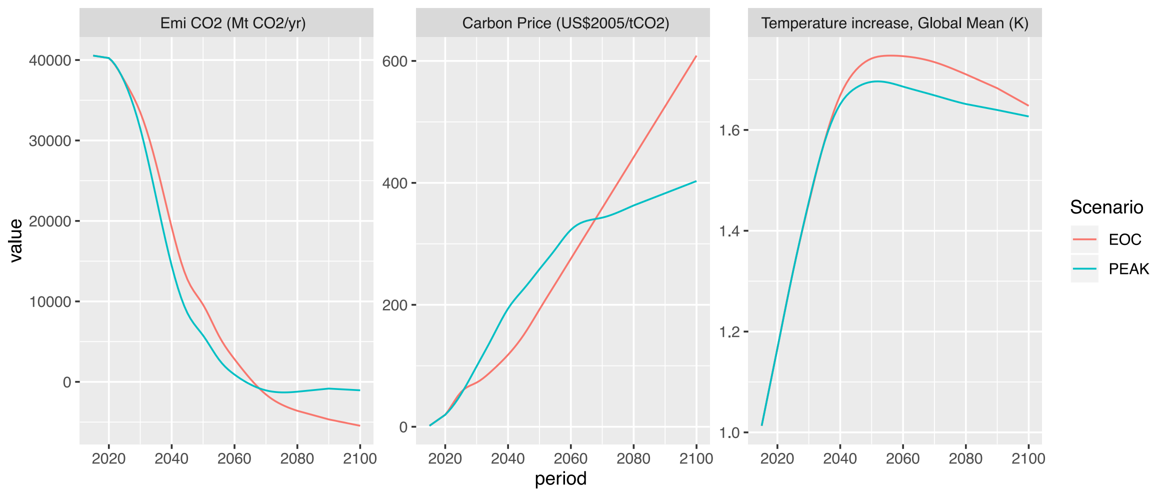

Fig. A.8. Differences between End-of-Century and Peak-budget scenarios.

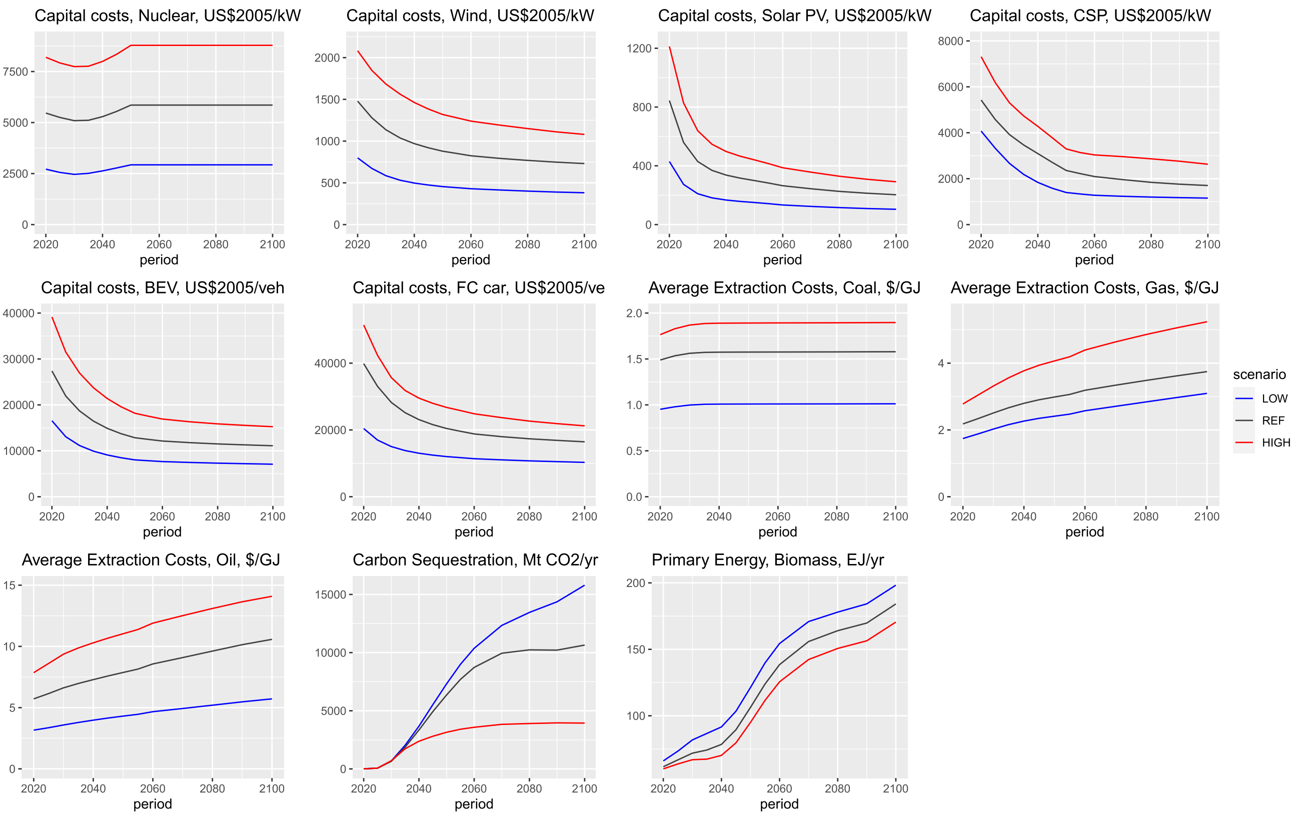

Fig. A.9. Technology cost ranges of the present study. Turnkey costs for solar photovoltaics, CSP, onshore wind, and nuclear power. Average extraction costs for fossil fuels, and purchase costs for hydrogen and electric vehicles. For biomass, the effect of the range in production cost is shown by means of primary energy usage. The CDR curve shows the uncertainty in the CCS injection rate. See section 2.2 for sources.

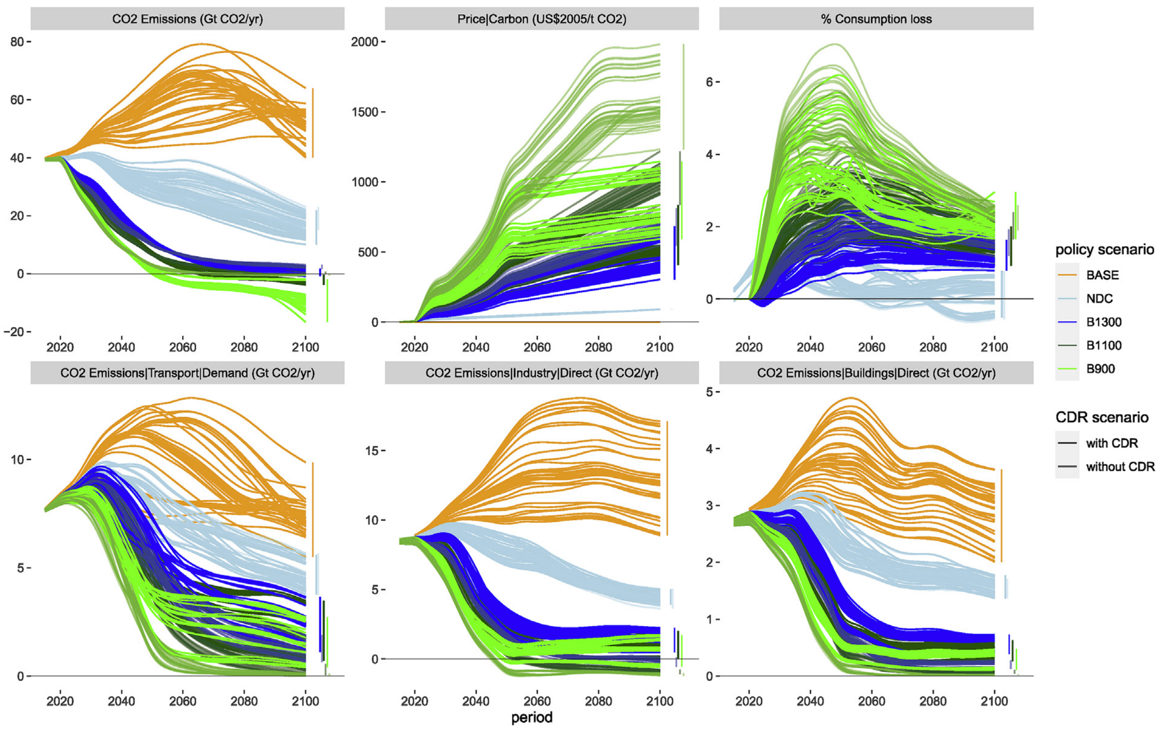

Fig. A.10. Ensemble showing all scenarios, with uncertainty ranges

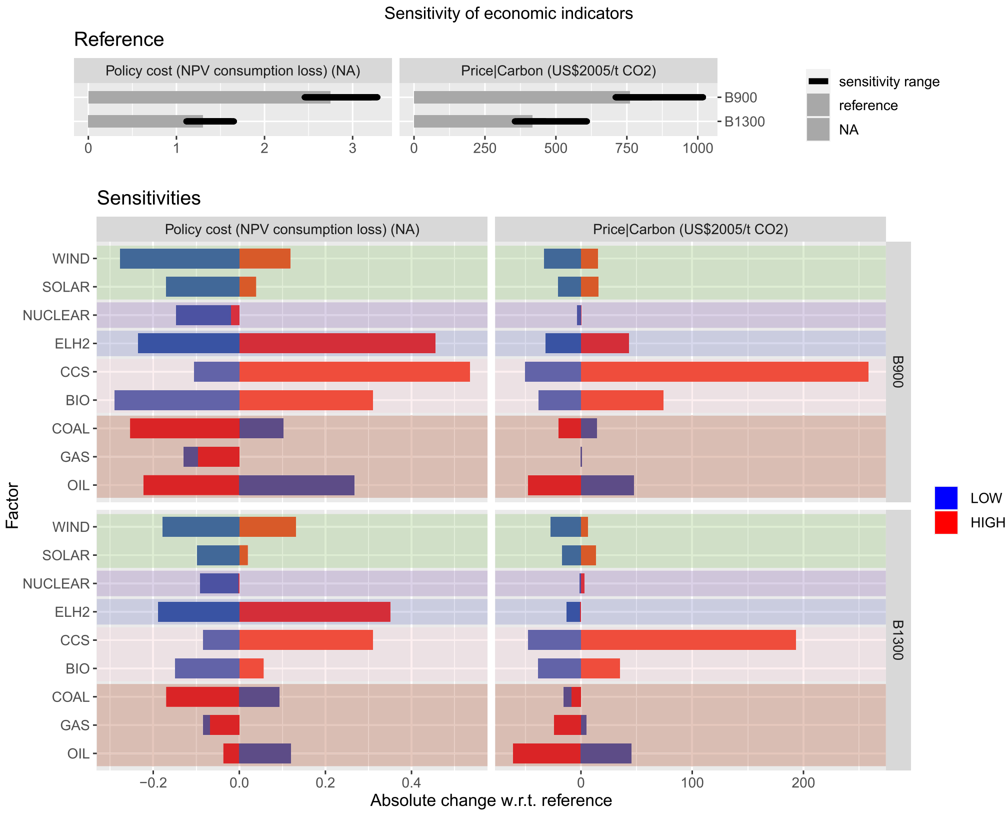

Fig. A.11. Modified tornado-diagrams: Economic indicators for additional policy scenarios. The Sensitivities panel shows absolute change (x axis) in mitigation indicators caused by one-factor-at-a-time variation of technology costs (y axis). Blue bars correspond to low cost, red bars to high (for the CCS injection rate—the only technology where a physical property rather than costs is varied—the colors are used to reflect how "accessible" the technology is, thus red is low rate and blue is high). Reference values (equal across factors) are shown with grey horizontal bars at the top, black lines show the sensitivity ranges. Example on how the information on the diagrams is interpreted: "cheap oil and expensive ELH2 lead to increased policy costs in a B900 scenario", etc. The policy costs are net present value consumption losses relative to the baseline, aggregated over the period 2010–2100 and discounted at 5%.

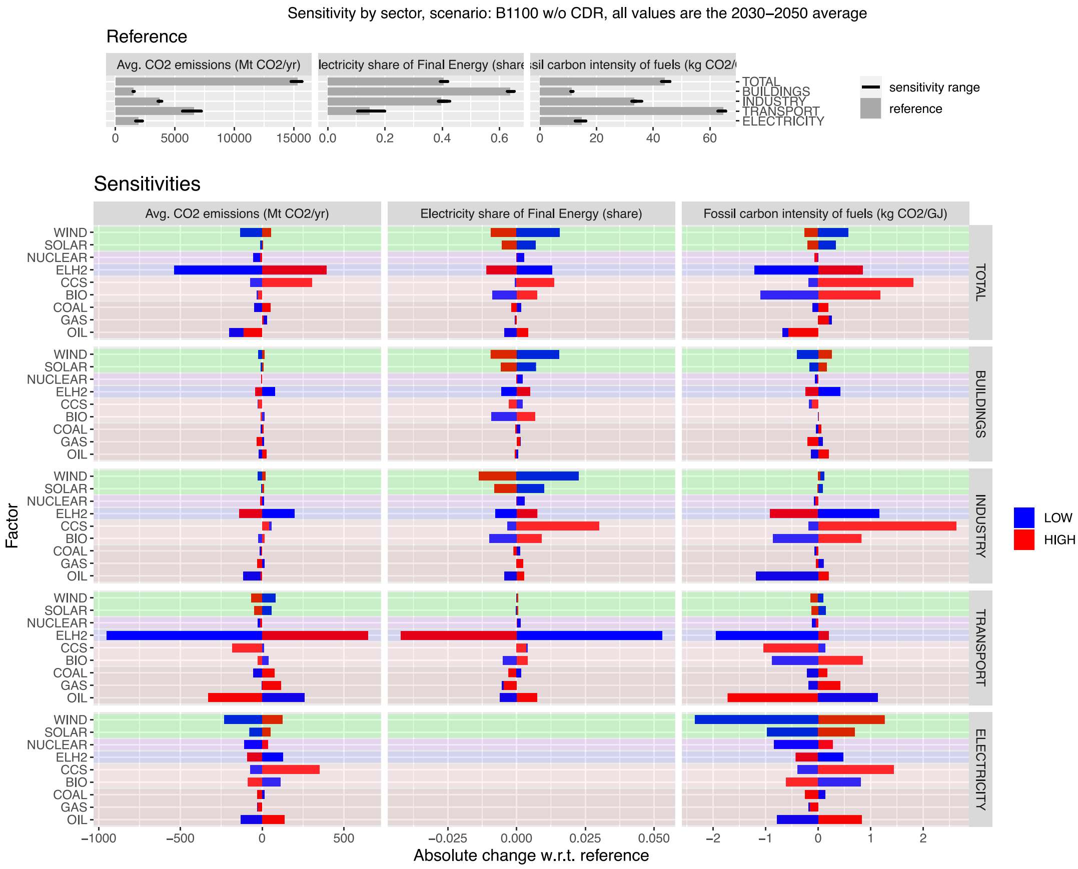

Figure A.12**Modified tornado-diagrams with sectoral detail, B1100 w/o CDR.** Absolute change (x axis) in the indicators describing the depth of decarbonization caused by one-factor-at-a-time variation of technology costs (y axis). Red bars correspond to high cost, blue bars to low. Reference values (equal across factors) are shown with grey horizontal bars at the top, black lines show the sensitivity ranges.

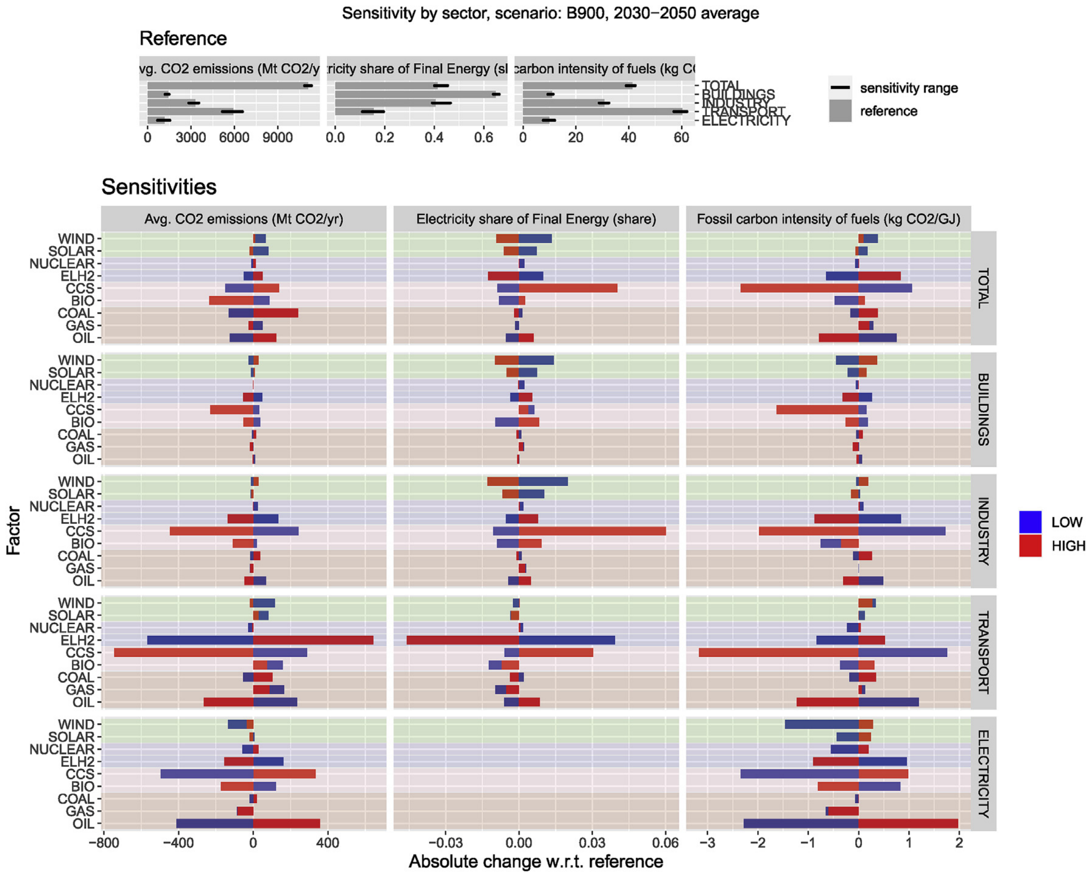

Fig. A.13. Modified tornado-diagrams with sectoral detail, B900. Absolute change (x axis) in the indicators describing the depth of decarbonization caused by one-factor-at-a-time variation of technology costs (y axis). Red bars correspond to high cost, blue bars to low. Reference values (equal across factors) are shown with grey horizontal bars at the top, black lines show the sensitivity ranges.

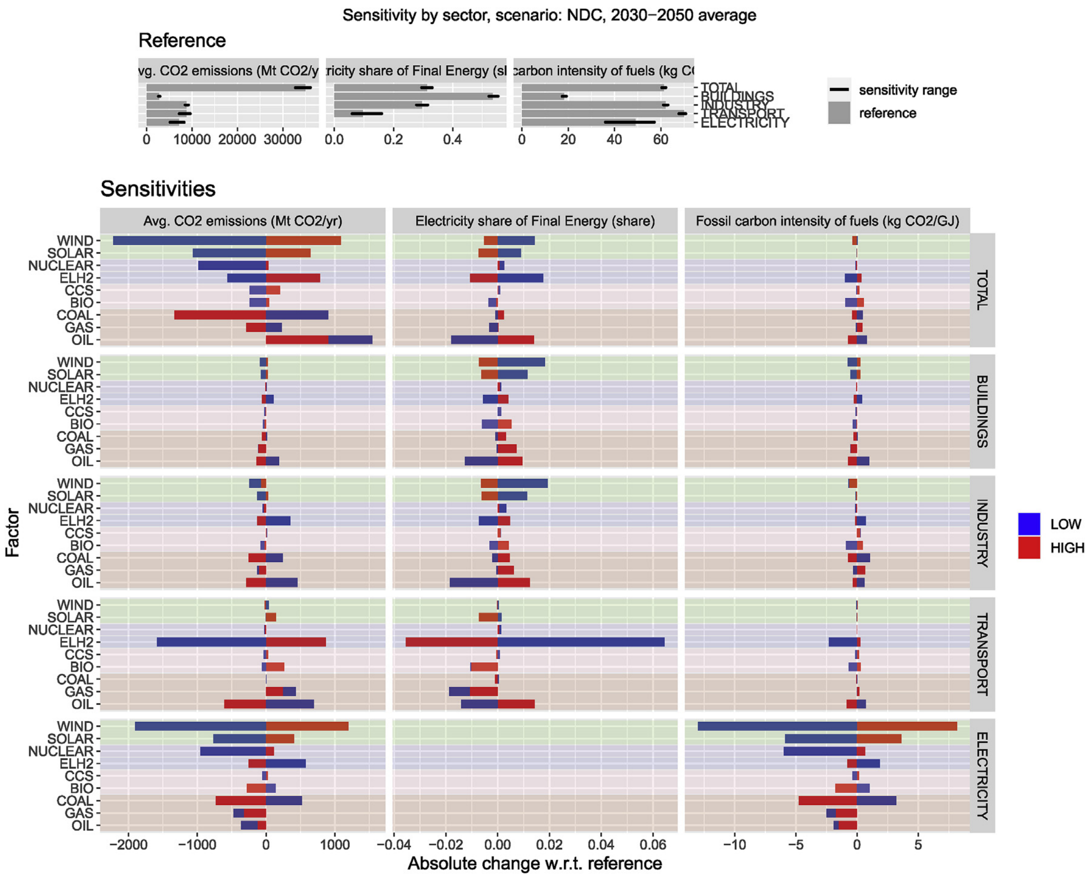

Fig. A.14. Modified tornado-diagrams with sectoral detail, NDC scenario. Absolute change (x axis) in the indicators describing the depth of decarbonization caused by one-factor-at-a-time variation of technology costs (y axis). Red bars correspond to high cost, blue bars to low. Reference values (equal across factors) are shown with grey horizontal bars at the top, black lines show the sensitivity ranges.

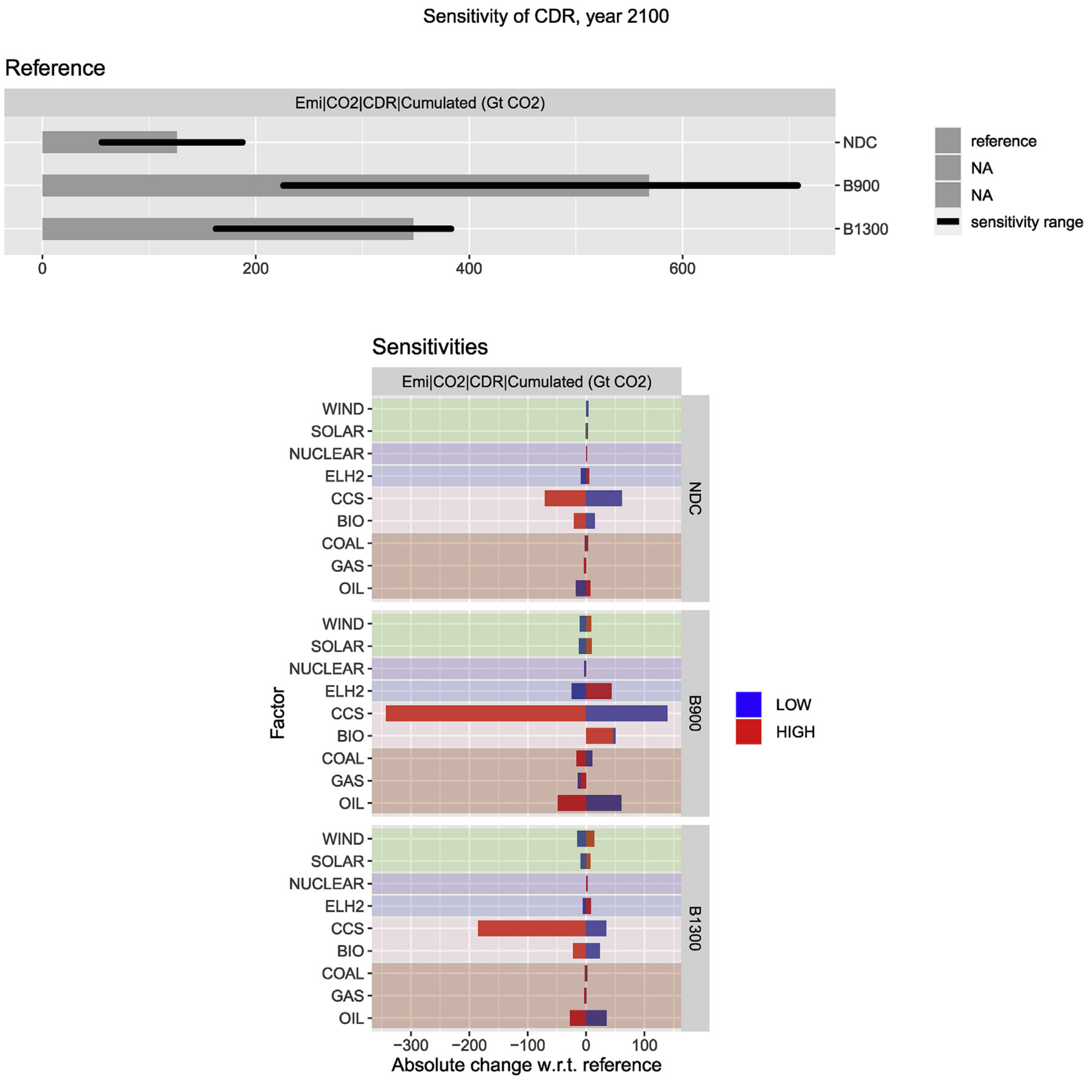

Fig. A.15. Modified tornado-diagram: CDR demand across policy scenarios. Absolute change (x axis) in the indicators describing the CDR demand caused by one-factor-at-a-time variation of technology costs (y axis). Red bars correspond to high cost, blue bars to low. Reference values (equal across factors) are shown with grey horizontal bars at the top, black lines show the sensitivity ranges.

References

[1] Papadis E, Tsatsaronis G. Challenges in the decarbonization of the energy sector. Energy 2020;205:118025. https://doi.org/10.1016/j.energy.2020.118025doi. http://www.sciencedirect.com/science/article/pii/S0360544220311324.

[2] Luderer G, Vrontisi Z, Bertram C, Edelenbosch OY, Pietzcker RC, Rogelj J, Boer HSD, Drouet L, Emmerling J, Fricko O, Fujimori S, HavlÃk P, Iyer G, Keramidas K, Kitous A, Pehl M, Krey V, Riahi K, Saveyn B, Tavoni M, Vuuren DPV, Kriegler E. Residual fossil CO 2 emissions in 1.5â€"2 Â°C pathways. Nat Clim Change 2018;8:626. https://doi.org/10.1038/s41558-018-0198-6. https://www.nature.com/articles/s41558-018-0198-6.

[3] Kumar P, Banerjee R, Mishra T. A framework for analyzing trade-offs in cost and emissions in power sector. Energy 2020;195:116949. https://doi.org/10.1016/j.energy.2020.116949. http://www.sciencedirect.com/science/article/pii/S0360544220300566.

[4] Kriegler E, Weyant JP, Blanford GJ, Krey V, Clarke L, Edmonds J, Fawcett A, Luderer G, Riahi K, Richels R, Rose SK, Tavoni M, Vuuren DPv. The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies. Climatic Change 2014;123:353–67. https://doi.org/10.1007/s10584-013-0953-7. http://link.springer.com/article/10.1007/s10584-013-0953-7.

[5] Pietzcker RC, Stetter D, Manger S, Luderer G. Using the sun to decarbonize the power sector: the economic potential of photovoltaics and concentrating solar power. Appl Energy 2014;135:704–20. https://doi.org/10.1016/j.apenergy.2014.08.011. http://www.sciencedirect.com/science/article/pii/S0306261914008149.

[6] Hirth L, Steckel JC. The role of capital costs in decarbonizing the electricity sector. Environ Res Lett 2016;11:114010. https://doi.org/10.1088/1748-9326/11/11/114010. https://doi.org/10.1088%2F1748-9326%2F11%2F11%2F114010.

[7] van Vuuren DP, van der Wijst KI, Marsman S, van den Berg M, Hof AF, Jones CD. The costs of achieving climate targets and the sources of uncertainty. In: Nature climate change. Nature Publishing Group; 2020. p. 1–6. https://doi.org/10.1038/s41558-020-0732-1. https://www.nature.com/articles/s41558-020-0732-1.

[8] Mouratiadou I, Luderer G, Bauer N, Kriegler E. Emissions and their drivers: sensitivity to economic growth and fossil fuel availability across world regions. Climatic Change 2015:1–15. http://doi.org/10.1007/s10584-015-1368-4, doi:10.1007/s10584-015-1368-4. 00000.

[9] Bosetti V, Catenacci M, Fiorese G, Verdolini E. The future prospect of PV and CSP solar technologies: an expert elicitation survey. Energy Pol 2012;49:308–17. https://doi.org/10.1016/j.enpol.2012.06.024. http://www.sciencedirect.com/science/article/pii/S0301421512005344.

[10] Candelise C, Winskel M, Gross RJK. The dynamics of solar PV costs and prices as a challenge for technology forecasting. Renew Sustain Energy Rev 2013;26:96–107. https://doi.org/10.1016/j.rser.2013.05.012. http://www.sciencedirect.com/science/article/pii/S1364032113003158.

[11] Labriet M, Kanudia A, Loulou R. Climate mitigation under an uncertain technology future: a TIAM-World analysis. Energy Econ 2012;34(Supplement 3):S366–77. https://doi.org/10.1016/j.eneco.2012.02.016.00030. http://www.sciencedirect.com/science/article/pii/S0140988312000461.

[12] Baker E, Bosetti V, Anadon LD, Henrion M, Aleluia Reis L. Future costs of key low-carbon energy technologies: harmonization and aggregation of energy technology expert elicitation data. Energy Pol 2015;80:219–32. https://doi.org/10.1016/j.enpol.2014.10.008. http://www.sciencedirect.com/science/article/pii/S0301421514005527.

[13] Bistline JET, Blanford GJ. Value of technology in the U.S. electric power sector: impacts of full portfolios and technological change on the costs of meeting decarbonization goals. Energy Econ 2020;86:104694. https://doi.org/10.1016/j.eneco.2020.104694. http://www.sciencedirect.com/science/article/pii/S0140988320300335.

[14] Wang H, Chen W, Zhang H, Li N. Modeling of power sector decarbonization in China: comparisons of early and delayed mitigation towards 2-degree target. Climatic Change 2019. https://doi.org/10.1007/s10584-019-02485-8.

[15] Liu X, Du H, Brown MA, Zuo J, Zhang N, Rong Q, Mao G. Low-carbon technology diffusion in the decarbonization of the power sector: policy implications. Energy Pol 2018;116:344–56. https://doi.org/10.1016/j.enpol.2018.02.001. http://www.sciencedirect.com/science/article/pii/S0301421518300715.

[16] Bertram C, Luderer G, Pietzcker RC, Schmid E, Kriegler E, Edenhofer O. Complementing carbon prices with technology policies to keep climate targets within reach. In: Nature climate change, vol. 5. Nature Publishing Group; 2015. p. 235–9. https://doi.org/10.1038/nclimate2514. https://www.nature.com/articles/nclimate2514.

[17] Tietjen O, Pahle M, Fuss S. Investment risks in power generation: a comparison of fossil fuel and renewable energy dominated markets. Energy Econ 2016;58:174–85. https://doi.org/10.1016/j.eneco.2016.07.005. http://www.sciencedirect.com/science/article/pii/S0140988316301773.

[18] Creutzig F, Agoston P, Goldschmidt JC, Luderer G, Nemet G, Pietzcker RC. The underestimated potential of solar energy to mitigate climate change. Nature Energy 2017;2:nenergy2017140. https://doi.org/10.1038/nenergy.2017.140. https://www.nature.com/articles/nenergy2017140.

[19] Knobloch F, Hanssen SV, Lam A, Pollitt H, Salas P, Chewpreecha U, Huijbregts MAJ, Mercure JF. Net emission reductions from electric cars and heat pumps in 59 world regions over time. In: Nature sustainability, vol. 3. Nature Publishing Group; 2020. p. 437–47. https://doi.org/10.1038/s41893-020-0488-7. 6, https://www.nature.com/articles/s41893-020-0488-7.

[20] van der Zwaan B, Keppo I, Johnsson F. How to decarbonize the transport sector? Energy Pol 2013;61:562–73. https://doi.org/10.1016/j.enpol.2013.05.118. http://www.sciencedirect.com/science/article/pii/S0301421513004734.

[21] Haasz T, GÃ³mez Vilchez JJ, Kunze R, Deane P, Fraboulet D, Fahl U, Mulholland E. Perspectives on decarbonizing the transport sector in the EU-28. Energy Strategy Reviews 2018;20:124–32. https://doi.org/10.1016/j.esr.2017.12.007. http://www.sciencedirect.com/science/article/pii/S2211467X17300858.

[22] Hoekstra A. The underestimated potential of battery electric vehicles to reduce emissions. Joule 2019;3:1412–4. https://doi.org/10.1016/j.joule.2019.06.002. http://www.sciencedirect.com/science/article/pii/S2542435119302715.

[23] Zimmer A, Koch N. Fuel consumption dynamics in Europe: tax reform implications for air pollution and carbon emissions. Transport Res Pol Pract 2017;106:22–50. https://doi.org/10.1016/j.tra.2017.08.006. http://www.sciencedirect.com/science/article/pii/S0965856416307650.

[24] Solaymani S. CO2 emissions patterns in 7 top carbon emitter economies: the case of transport sector. Energy 2019;168:989–1001. https://doi.org/10.1016/j.energy.2018.11.145. http://www.sciencedirect.com/science/article/pii/S0360544218323569.

[25] Bosetti V, Marangoni G, Borgonovo E, Diaz Anadon L, Barron R, McJeon HC, Politis S, Friley P. Sensitivity to energy technology costs: a multi-model comparison analysis. Energy Pol 2015;80:244–63. https://doi.org/10.1016/j.enpol.2014.12.012. http://www.sciencedirect.com/science/article/pii/S0301421514006776.

[26] Saltelli A, Bammer G, Bruno I, Charters E, Fiore MD, Didier E, et al. Five ways to ensure that models serve society: a manifesto. In: Nature, vol. 582. Nature Publishing Group; 2020. p. 482–4. https://doi.org/10.1038/d41586-020-01812-9. number: 7813 Publisher, https://www.nature.com/articles/d41586-020-01812-9.

[27] Drouet L, Bosetti V, Tavoni M. Selection of climate policies under the uncertainties in the fifth assessment report of the IPCC. Nat Clim Change 2015;5:937–40. https://doi.org/10.1038/nclimate2721. http://www.nature.com/nclimate/journal/v5/n10/full/nclimate2721.html?foxtrotcallback=true.

[28] Rogelj J, Huppmann D, Krey V, Riahi K, Clarke L, Gidden M, Nicholls Z, Meinshausen M. A new scenario logic for the Paris Agreement long-term temperature goal. Nature 2019;573:357–63. https://doi.org/10.1038/s41586-019-1541-4. https://www.nature.com/articles/s41586-019-1541-4.

[29] Strefler J, Luderer G, Kriegler E, Bauer N, Pietzcker R, Giannousakis A, et al. Alternative carbon price trajectories can avoid excessive carbon removal. Springer Nature; 2020. Submitted for publication.

[30] Bauer N, Hilaire J, Brecha RJ, Edmonds J, Jiang K, Kriegler E, Rogner HH, Sferra F. Assessing global fossil fuel availability in a scenario framework. Energy 2016;111:580–92. https://doi.org/10.1016/j.energy.2016.05.088.00002. http://www.sciencedirect.com/science/article/pii/S0360544216307058.

[31] IRENA. Renewable power generation costs in 2018. Technical report. Abu Dhabi: International Renewable Energy Agency; 2019.

[32] Cox B, Mutel CL, Bauer C, Mendoza Beltran A, van Vuuren DP. Uncertain environmental footprint of current and future battery electric vehicles. Environ Sci Technol 2018;52:4989–95. https://doi.org/10.1021/acs.est.8b00261.

[33] Rogner HH. An assessment of world hydrocarbon ressources. Annu Rev Energy Environ 1997;22:217–62. https://doi.org/10.1146/annurev.energy.22.1.217. http://arjournals.annualreviews.org/doi/abs/10.1146/annurev.energy.22.1.217.

[34] Rogner HH, Aguilera RF, Bertani R, Bhattacharya S, Dusseault MB, Gagnon L, Haberl H, Hoogwijk M, Johnson A, Rogner ML, Wagner H, Yakushev V. Chapter 7 - energy resources and potentials. In: Global energy assessment - toward a sustainable future. Cambridge, UK and New York, NY, USA and the International Institute for Applied Systems Analysis, Laxenburg, Austria: Cambridge University Press; 2012. p. 423–512. www.globalenergyassessment.org.

[35] Herfindahl OC. Depletion and economic theory. In: Gaffney M, editor. Extractive resources and taxation. Madison, Wisconsin: University of Wisconsin Press; 1967.

[36] Aguilera RF, Eggert RG, C C GL, Tilton JE. Depletion and the future availability of petroleum resources. Energy J 2009;30:141–74. http://econpapers.repec.org/article/aenjournl/2009v30-01-a06.htm.

[37] Bauer N, Bosetti V, Hamdi-Cherif M, Kitous A, McCollum D, MÃ©jean A, Rao S, Turton H, Paroussos L, Ashina S, Calvin K, Wada K, van Vuuren D. CO2 emission mitigation and fossil fuel markets: dynamic and international aspects of climate policies. Technol Forecast Soc Change 2015;90:243–56. https://doi.org/10.1016/j.techfore.2013.09.009.00000. http://www.sciencedirect.com/science/article/pii/S0040162513002382.

[38] Klein D, HumpenÃ¶der F, Bauer N, Dietrich JP, Popp A, Bodirsky BL, Bonsch M, Lotze-Campen H. The global economic long-term potential of modern biomass in a climate-constrained world. Environ Res Lett 2014;9:074017.

[39] Krey V, Guo F, Kolp P, Zhou W, Schaeffer R, Awasthy A, Bertram C, de Boer HS, Fragkos P, Fujimori S, He C, Iyer G, Keramidas K, KÃ¶berle AC, Oshiro K, Reis LA, Shoai-Tehrani B, Vishwanathan S, Capros P, Drouet L, Edmonds JE, Garg A, Gernaat DEHJ, Jiang K, Kannavou M, Kitous A, Kriegler E, Luderer G, Mathur R, Muratori M, Sano F, van Vuuren DP. Looking under the hood: a comparison of techno-economic assumptions across national and global

integrated assessment models. Energy 2019;172:1254–67. https://doi.org/10.1016/j.energy.2018.12.131. http://www.sciencedirect.com/science/article/pii/S0360544218325039.

[40] Marangoni G, Tavoni M, Bosetti V, Borgonovo E, Capros P, Fricko O, Gernaat DEHJ, Guivarch C, Havlik P, Huppmann D, Johnson N, Karkatsoulis P, Keppo I, Krey V, Â“ Broin E, Price J, van Vuuren DP. Sensitivity of projected long-term CO2 emissions across the shared socioeconomic pathways. Nat Clim Change 2017;7:113–7. https://doi.org/10.1038/nclimate3199. http://www.nature.com/nclimate/journal/v7/n2/full/nclimate3199.html#contrib-auth.

[41] Borgonovo E. A methodology for determining interactions in probabilistic safety assessment models by varying one parameter at a time. Risk Anal 2010;30:385–99. https://doi.org/10.1111/j.1539-6924.2010.01372.x. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1539-6924.2010.01372.x. https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1539-6924.2010.01372.x.

[42] Homma T, Saltelli A. Importance measures in global sensitivity analysis of nonlinear models. Reliab Eng Syst Saf 1996;52:1–17. https://doi.org/10.1016/0951-8320(96)00002-6. http://www.sciencedirect.com/science/article/pii/0951832096000026.

[43] Luderer G, Pietzcker RC, Bertram C, Kriegler E, Meinshausen M, Edenhofer O. Economic mitigation challenges: how further delay closes the door for achieving climate targets. Environ Res Lett 2013;8:034033. https://doi.org/10.1088/1748-9326/8/3/034033. http://iopscience.iop.org/1748-9326/8/3/034033.

[44] Luderer G, Leimbach M, Bauer N, Kriegler E, Baumstark L, Bertram C, Giannousakis A, Hilaire J, Klein D, Levesque A, Mouratiadou I, Pehl M, Pietzcker R, Piontek F, Roming N, Schultes A, Schwanitz VJ, Strefler J. Description of the REMIND model. In: Social science research network. Rochester, NY; 2015. SSRN Scholarly Paper ID 2697070, Version 1.6. https://papers.ssrn.com/abstract=2697070.

[45] IPCC. Climate change 2014: synthesis report. Contribution of working groups I, II and III to the fifth assessment report of the intergovernmental panel of climate change. Technical Report; 2014.

[46] IPCC. Global warming of 1.5Â°C. An IPCC Special Report on the impacts of global warming of 1.5Â°C above pre-industrial levels and related global greenhouse gas emission pathways. In: The context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. Technical Report; 2018.

[47] Pietzcker RC, Ueckerdt F, Carrara S, de Boer HS, DesprÃ©s J, Fujimori S, et al. System integration of wind and solar power in integrated assessment models: a cross-model evaluation of new approaches. Energy Econ 2017;64:583–99. https://doi.org/10.1016/j.eneco.2016.11.018. http://www.sciencedirect.com/science/article/pii/S0140988316303395.

[48] Bauer N, Rose SK, Fujimori S, van Vuuren DP, Weyant J, Wise M, Cui Y, Daioglou V, Gidden MJ, Kato E, Kitous A, Leblanc F, Sands R, Sano F, Strefler J, Tsutsui J, Bibas R, Fricko O, Hasegawa T, Klein D, Kurosawa A, Mima S, Muratori M. Global energy sector emission reductions and bioenergy use: overview of the bioenergy demand phase of the EMF-33 model comparison. Climatic Change 2018. https://doi.org/10.1007/s10584-018-2226-y.

[49] Riahi K, van Vuuren DP, Kriegler E, Edmonds J, Oâ€™Neill BC, Fujimori S, Bauer N, Calvin K, Dellink R, Fricko O, Lutz W, Popp A, Cuaresma JC, KC S, Leimbach M, Jiang L, Kram T, Rao S, Emmerling J, Ebi K, Hasegawa T, Havlik P, HumpenÃ¶der F, Da Silva LA, Smith S, Stehfest E, Bosetti V, Eom J, Gernaat D, Masui T, Rogelj J, Strefler J, Drouet L, Krey V, Luderer G, Harmsen M, Takahashi K, Baumstark L, Doelman JC, Kainuma M, Klimont Z, Marangoni G, Lotze-Campen H, Obersteiner M, Tabeau A, Tavoni M. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: an overview. Global Environ Change 2017;42:153–68. https://doi.org/10.1016/j.gloenvcha.2016.05.009. http://www.sciencedirect.com/science/article/pii/S0959378016300681.

[50] O'Neill BC, Kriegler E, Riahi K, Ebi KL, Hallegatte S, Carter TR, et al. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Climatic Change 2014;122:387–400. https://doi.org/10.1007/s10584-013-0905-2. http://link.springer.com/article/10.1007/s10584-013-0905-2.

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Socioeconomic Uncertainty and Burden Sharing of Climate Change Mitigation *

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Burden sharing of climate change mitigation: global and regional challenges under shared socio-economic pathways

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Abstract
We analyze the burden sharing of climate stabilization under socio-economic scenario uncertainty and for various burden-sharing regimes. For this purpose, we quantify mitigation efforts in terms of emission reductions and mitigation costs for a number of major world regions, considering scenarios with and without climate finance. The influence of socio-economic drivers on the burden sharing is crucial, but it has not yet been studied in the context of the most recent scenario framework—the shared socio-economic pathway scenarios (SSPs). Here, we show that sustainable development as represented by the SSP1 scenario reduces the challenges of burden sharing and makes it easier to achieve equitable climate policies. In contrast, in a scenario with fossil-fueled development (SSP5), the risk of political infeasibility—measured by the variation of mitigation costs across regions and the amount of implied international transfers—increases with most burden-sharing regimes.

1 Introduction

The current climate policy (Paris Agreement) focuses on national contributions (NDCs) and early entry points of action, but recent studies (e.g., Robiou du Pont et al. 2017; Rogelj et al. 2017; Kriegler et al. 2018; Vrontisi et al. 2018) show that greenhouse gas (GHG) emission reductions in line with NDCs will not be sufficient to achieve a long-term climate stabilization below 2 °C. Unilateral emission reductions need to be intensified in ambition and likely be followed by multilateral action. Yet, efforts to implement an ambitious multilateral reduction plan will only be successful if the overall burden sharing meets certain fairness criteria. The

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principle of Common but Differentiated Responsibilities, as a cornerstone of sustainable development, holds also for climate policies and is thus included in the Paris Agreement (UNFCCC 2015). The goal-oriented use of instruments that support international climate policy, such as climate finance and emissions trading, could help improve the efficiency, while at the same time increase the fairness of mitigation measures. The burden sharing across countries will likely differ with the level of global mitigation, and its perceived equity depends on the dynamics of climate change and its socio-economic drivers. The newly developed shared socio-economic pathway scenarios (O'Neill et al. 2014) provide a useful tool to consider the uncertainty in the future development of these drivers.

The burden sharing of climate stabilization and the feasibility of fair burden-sharing regimes have not yet been studied in the context of the SSPs. In this paper, we do so and contribute to the existing literature by comparing the mitigation burden sharing of a 2 °C climate stabilization in different socio-economic futures represented by the scenarios SSP1 ("sustainable development"), SSP2 ("middle-of-the-road"), and SSP5 ("fossil-fueled development"). In the absence of climate finance, developing countries would face rather high costs (cf. Tavoni et al. 2015), which conflicts with the principle of Common but Differentiated Responsibilities.[1] We address the underlying fairness dimension by contrasting carbon tax scenarios with cap-and-trade scenarios based on different permit allocation schemes. We quantify the burden sharing of mitigation across a number of major world regions, while using the term burden sharing for both the sharing of financial burdens (mitigation costs and financial transfers) and mitigation efforts (emission reduction levels). Furthermore, we evaluate the burden-sharing scenarios with regard to their chances of implementation (i.e., political feasibility) based on their contribution to the equalization of mitigation costs and the requirements of climate finance across regions. In a next step, by decomposing mitigation costs, we identify components that contribute differently to the cost magnitude across regions and to the cost shares in each region across the SSPs. This decomposition addresses the sensitivity of the mitigation costs to a number of socio-economic and techno-economic parameters and assumptions. Our results provide meaningful information for climate policy-makers on how to design future policy regimes and how to implement and direct financial transfers.

The paper is structured as follows. In Section 2, we discuss the existing literature on the burden sharing of climate change mitigation. The analysis in this study is performed by applying the integrated assessment model REMIND, followed by an ex-post analysis of model results. The model and the experimental design are presented in Section 3. In presenting results, we start in Section 4 with comparing global mitigation levels and costs across different SSPs. In Section 5, we discuss the regional allocation of mitigation efforts. We quantify the level of emission reduction each region has to provide according to the globally cost-effective emission reduction strategy and contrast it to the amount of permits each region is allocated under different burden-sharing regimes. Furthermore, we quantify the mitigation costs of the burden-sharing regimes and evaluate these regimes along criteria of political feasibility. Equality-based burden sharing schemes perform quite well and are subsequently subject to an in-depth analysis including a decomposition of the implied mitigation costs across different SSP scenarios in Section 6. We conclude in Section 7.

[1] The principle of Common but Differentiated Responsibilities (as stated in the Framework Convention on Climate Change) requests all parties to act on the basis of equality. While all countries are responsible for protecting the climate system, the level of action should respect national differences of capabilities to avoid unwarranted social costs in particular for developing countries.

2 Literature

The literature on international burden sharing of climate change mitigation is rich with fairness playing a major role in most studies (Rose et al. 1998; Berk and den Elzen 2001; den Elzen et al. 2005; Ekholm et al. 2010; Hof et al. 2010; Leimbach et al. 2010; Lüken et al. 2011; Luderer et al. 2012; Aboumahboub et al. 2014; Höhne et al. 2014; Raupach et al. 2014; Tavoni et al. 2015; Herrala and Goel 2016; Robiou du Pont et al. 2017). An appropriate setting to investigate burden sharing is provided by the cap-and-trade systems. In such systems, countries are entitled to greenhouse gas emissions by an agreed initial allocation of allowances. The burden sharing is a result of this allocation. The higher the share of allocated permits, the lower the relative burden is. This mitigation burden can be reduced Pareto efficiently by the trade of emission permits. Rose et al. (2017) identify mitigation cost savings of 77% when the national reduction pledges in the Paris Agreement are combined with an emission trading system. Extreme emission reduction rates, e.g., 15% per year for North America under a 2 °C scenario and an equity-based allocation of emission quotas—as computed by Raupach et al. (2014)—could be avoided by emissions trading. The problem of distributing emission permits, however, cannot be fully solved by economic criteria, because emissions trading yields Pareto efficiency irrespective of the initial distribution of emission permits (Rose and Stevens 1993; Manne and Stephan 2005). This holds under certain conditions in theory and will roughly take effect in this way in reality despite existing market failures. "Where-flexibilty" and the separation of equity and efficiency in emissions reduction follow Coase (1960), who addressed the assignment of property rights as an efficient solution to market externalities. While this leads to equal marginal costs of emission reduction across countries, regional mitigation cost levels vary across countries depending on the applied burden-sharing rules.

The literature studies several burden-sharing schemes with benefits varying across countries and regions. Recent overviews on burden-sharing schemes (also called effort-sharing approaches) are provided by den Elzen et al. (2010), van Ruijven et al. (2012), Höhne et al. (2014), and Zhou and Wang (2016). As fairness turned out to be a key component of climate policy agreements and the lack thereof a major barrier in current and past negotiations, a number of studies focus on equity-based principles of burden sharing, e.g., Rose and Stevens (1993), Kverndokk (1995), Metz (2000), Vaillancourt and Waaub (2004), Markandya (2011), Mattoo and Subramanian (2012), Klinsky and Winkler (2014), Kverndokk (2018), and Leimbach et al. (2018). Lange et al. (2010) find out that even with self-interested agents, equity arguments are used, for example, in order to facilitate negotiations. While the burden-sharing schemes mostly rely on the initial allocation of emission permits, Böhringer and Helm (2008) focus on a fair division of the efficiency gains that arise from exchanging permits. Gerlagh (2007), furthermore, addresses the burden-sharing issue not only as an interregional but also as an intergenerational issue.

Several previous studies on mitigation burden sharing investigated the influence of different permit allocation rules in scenarios aiming at achieving different climate stabilization targets. But, while Marangoni et al. (2017) identify energy intensity and economic growth as major factors that explain the uncertainty of CO_2 projections, the influence of these socio-economic drivers on the burden sharing has rarely been studied. Ekholm et al. (2010) have done this based on the SRES scenarios. In few other studies, sensitivity analyses have been carried out by varying growth rates of GDP and population and by varying elasticity parameters or the availability of technologies (e.g., Yohe and van Engel 2004; Lüken et al. 2011; Aboumahboub et al. 2014). The present study contributes to the literature by investigating the impact of socio-economic drivers and conditions on the burden sharing of climate change mitigation based on a robust approach. In this approach, we take into account the interdependency of socio-economic factors represented by the new SSP scenarios (Riahi et al. 2017). These scenarios provide quantitative projections based on five narratives of alternative socio-economic developments (O'Neill et al. 2014) and a consistent compilation and implementation of economic, demographic, energy-related, and land use-related model assumptions. While the present study covers uncertainty on socio-economic drivers, it does not cover uncertainty that is represented by model assumptions and properties. In this latter respect, we refer to an effort-sharing analysis by van den Berg et al. (2019) which covers a broad range of uncertainty of model parameters. In contrast to the present study, van den Berg et al. (2019) do not address the cost dimension of burden sharing, but put a stronger focus on domestic reduction efforts within burden-sharing schemes.

To our knowledge, our study is the first that addresses the burden-sharing dimension in the framework of the new SSP scenarios. Apart from this novelty, this study puts an aspect into the focus—regional mitigation costs—that so far has not received much attention in the analysis of mitigation scenarios within the SSP context. The SSP overview paper by Riahi et al. (2017) does provide a brief summary of global average mitigation costs, but no indication is given how the costs spread across different countries or world regions. By quantifying regional mitigation costs, this study also goes beyond of what most studies that analyze burden-sharing regimes usually do: comparing emission reduction efforts. Even if we admit that the quantification of regional mitigation costs is subject to uncertainties, in relative terms they characterize the cost implications of different burden-sharing regimes quite well and allow concluding on their political feasibility. The attempt to evaluate the political feasibility of burden-sharing regimes and, in addition, a new scenario of constraining mitigation costs are further contributions of this study to the literature.

3 Model and experimental design

We perform the burden-sharing analysis by the use of the integrated assessment model REMIND, followed by an ex-post analysis. REMIND features verified ability to analyze SSP scenarios (Kriegler et al. 2017). It is a global, multi-regional, energy-economy-climate model (Leimbach et al. 2010). A detailed model description is provided by Luderer et al. (2015) and a summary is given in section A.1 of the Supplementary Material.

The version of REMIND applied here divides the world into eleven model regions: Sub-Saharan Africa (AFR), China, EU-28 (EUR), India, Japan, Latin America (LAM), Middle East and North Africa (MEA), Other Asia (OAS), Russia, the USA, and Rest of the World (ROW). As a measure of burden sharing, we compute the mitigation cost of each region defined as discounted aggregated consumption losses[2] of a mitigation scenario compared with the respective baseline scenario without climate policy. The computation of mitigation costs is based on a welfare-optimal solution that meets a given climate target cost-effectively. As usual

[2] Mitigation costs are measured in percent of baseline consumption discounted by the internal discount rate. Most mitigation cost analyses use an exogenous discount rate (usually 5%). This introduces an imprecision that is avoided by the current approach. Major component of the discount rate is the pure rate of time preference. As in most other comparable models, we use the same rate of time preference for all regions. We apply a value of 3%.

in the cost-effectiveness mode, damage costs and benefits of avoided climate damages are not additionally taken into account.

The current model implementation allows REMIND to analyze SSP1, SSP2, and SSP5 scenarios. We run for each SSP a baseline scenario that assumes the absence of climate policy and a set of mitigation scenarios (see Table 1) that all keep the radiative forcing level below 2.6 W/m^2 in 2100. This forcing target implies a high probability for keeping the increase of the global mean temperature below 2 °C (compared with the pre-industrial level).

Commonly, SSP-based mitigation scenarios include additional policy assumptions called shared policy assumptions (SPAs) (see Kriegler et al. 2014). We follow the SPA benchmark scenarios. They start from a fragmented policy regime with different regional carbon taxes and include a transition phase between 2025 and 2040 towards a climate policy regime with a uniform global carbon tax. We include this scenario type (**TAX**) as a reference policy scenario. Most integrated assessment studies restrict the analysis of mitigation effort sharing on results from this scenario type, thus giving a rather limited perspective on the burden-sharing dimension. The burden-sharing analysis in this study explores scenarios that assume a global cap-and-trade system succeeding the fragmented policy regime in 2025. The cap-and-trade systems are based on a set of permit allocation rules. Permit trading implies financial transfers on the carbon market that we consider as representative for any form of climate finance that lead to a cost-optimal allocation of emission reductions. In this study, reduction efforts as well as mitigation costs of each policy scenario are measured in comparison with the baseline scenario. This is in contrast to other studies on burden-sharing regimes that relate reduction efforts to a given emission level in a reference year (e.g., Höhne et al. 2014; Robiou du Pont et al. 2017).

Table 1 provides an overview of the permit allocation schemes. They represent a selection of allocation schemes frequently discussed in the literature (cf. van Ruijven et al. 2012; Höhne et al. 2014; Zhou and Wang 2016) and linked to the equity principles categorized by IPCC's Fifth Assessment Report (IPCC, WG III, p. 318 f.).

The contraction and convergence (**CC**) scheme (Meyer 2000) allocates global emission permits (determined by the globally optimal emission trajectory) in proportion to the weighted average of each region's share in global emissions in 2005 and an equal per capita share. Weights of the per capita share increase linearly over time. As of 2050, permits are allocated to the regions according to the equal per capita rule only. The equal effort-sharing (**EC**) scheme is aimed at adjusting the mitigation costs across regions (see Supplementary Material A.2). According to the grandfathering (**GF**) principle, regions are allocated with a share of permits

Table 1 Applied scenarios and burden-sharing schemes

	Scenario name			Equity principle/ IPCC category	Type of analysis
	SSP1	SSP2	SSP5		
Baseline					Simulation
Carbon tax (TAX)	SSP1-TAX	SSP2-TAX	SSP5-TAX		Simulation
Contraction and convergence (CC)	SSP1-CC	SSP2-CC	SSP5-CC	Capability and equality	Simulation
Population share (POP)	SSP1-POP	SSP2-POP	SSP5-POP	Equality	Simulation
Equal effort sharing (EC)	SSP1-EC	SSP2-EC	SSP5-EC	Equality	Ex-post
Grandfathering (GF)	SSP1-GF	SSP2-GF	SSP5-GF	Sovereignty	Ex-post
GDP intensity (GI)	SSP1-GI	SSP2-GI	SSP5-GI	Capability/Need	Ex-post
Historic responsibility (HR)	SSP1-HR	SSP2-HR	SSP5-HR	Responsibility	Ex-post
Equal per capita (PC)	SSP1-PC	SSP2-PC	SSP5-PC	Equality	Ex-post

that corresponds to their share on global GHG emissions in 2005, while the GDP intensity (**GI**) principle allocates permits equal to the share of each region on global GDP. Historical responsibility (**HR**) is measured as the contribution of each region to the temperature increase in 2005 and applies data from MATCH (2017). Corresponding data are also used by Höhne et al. (2011). Section A.3 of the Supplementary Material provides the details of how the permit emission share is calculated for this scheme. In the equal per capita (**PC**) scheme, each region receives emission permits in proportion to its projected population in each year. The population share (**POP**) scheme is based on a different rule of equal per capita allocation. The share S of region r in global permits is based on the cumulative population share over the twenty-first century ($t = 1, \ldots, T$):

$$S_r = \frac{\sum_t P_{r,t}}{\sum_t \sum_r P_{r,t}}$$

Population values $P_{r,\,t}$ are determined by the SSP population scenarios (KC and Lutz 2017).

In line with the motivation of this study, we select several burden-sharing schemes that are based on equity principles. There is "no absolute standard of equity" (IPCC 2014, p. 317) and no direct way of quantifying the equity of burden-sharing regimes. Yet, there is certainly a different degree of fairness associated with each scheme, which can be described in a qualitative way and which certainly plays an important role in the political discussion.

In this study, we attempt to additionally contribute to the discussion on what the appropriate burden-sharing regime might be by deriving quantitative indicators of political feasibility. We select two criteria that both address concerns of international negotiations and are accessible within the applied methodological framework of this study. A first concern relates to the distribution of mitigation costs. A high divergence of mitigation costs across countries is assumed to decrease the acceptance and feasibility of climate protocols. Second, huge amount of transfers (e.g., implied by emission trading regimes) are often seen as barriers for implementing equity-based burden sharing.[3] Consequently, in operationalizing the aspect of political feasibility, we evaluate two indicators:

- Volume of carbon trade costs/revenues
- Deviation of regional mitigation costs

We classify the burden-sharing schemes according to these two criteria and in addition investigate in how far the respective characteristics of burden-sharing regimes vary across different SSP scenarios.

In mitigation scenarios with no climate finance (TAX), regions enact carbon pricing in accordance with the abovementioned shared policy assumptions and a globally uniform carbon tax from 2040 on. There is neither an allocation of emission permits nor any other kind of financial transfer between model regions. To arrive at a cost-effective solution, we compute these scenarios by using exponentially rising global carbon tax paths compatible with the climate target.

[3] The evaluation of transfers is mixed (Kverndokk 2018). Limited and purposeful transfers can certainly facilitate climate agreements as climate finance is part of the UNFCCC. But at the same time, we see resistance regarding some forms of transfers, for example, development aid. This resistance is assumed to be increased with the level of transfers. In addition, high transfers on the carbon market bear institutional challenges like the climate rent curse (Kornek et al. 2017).

The climate finance scenarios assume an explicit burden-sharing scheme as part of an international climate agreement. In these scenarios, emission permits are allocated to regions in accordance with the burden-sharing scheme as well as with the climate target. Once allocated, emission permits can be traded in our model and generate—as a particular form of climate finance—revenues for permit selling regions. Technically, we compute the cost-effective solution by distributing a global permit budget compatible with the forcing target to regions and making sure that the permit market clears.

While we run some of the scenarios directly with REMIND in order to generate further results that we analyze in Section 6, for most of the burden-sharing regimes, we derive the desired results based on an ex-post analysis. This part of the assessment makes use of model output from REMIND and builds on a feature that a number of integrated assessment models are associated with: the separation of efficiency and equity (Rose and Stevens 1993; Manne and Stephan 2005; Luderer et al. 2012). This feature results in a pattern of regional technology portfolios and emissions that does not depend on the allocation of emission permits. Moreover, the resulting carbon price is also nearly independent of the permit allocation. The revenues on the carbon market represent income that does not change the investment structure but solely increases the consumption level.[4] Analytical details of the method underlying the ex-post analysis are given in the Supplementary Material (A.4).

4 Global mitigation level and costs across SSPs

The present study analyzes the sharing of mitigation efforts in ambitious climate stabilization scenarios (2.6 W/m^2) based on cost-optimal global emission trajectories. Figure 1 shows the emission trajectories of baseline and policy scenario runs of each SSP. Mitigation gaps between respective baseline and policy scenarios vary significantly across the SSPs. Differences in resulting mitigation costs can be expected.

Under ambitious climate stabilization scenarios, the SSP1-TAX scenario exhibits costs of around 0.8% of consumption. The costs are more than double in SSP2-TAX (1.8%) and triple in SSP5-TAX (2.4%). Due to the separation of efficiency and equity (see Section 3), the global mitigation costs are the same for the climate finance scenarios. The cost figures mirror the mitigation challenges that the different socio-economic pathways are linked with (O'Neill et al. 2014). In a world that respects environmental boundaries (SSP1), a less energy and carbon intensive way of production and moderate economic growth result in a relatively small mitigation gap. Comparatively low additional efforts are needed to close this gap. On the other hand, in a world with high economic growth fueled by fossil fuels (SSP5), baseline emissions are huge and the mitigation challenge is large.

The conclusion of the Fifth Assessment Report (AR5) of the IPCC that global costs increase with the ambition of the mitigation goal (IPCC 2014) applies to the present results if we take the mitigation gap (mitigation challenge) in the evaluation of the mitigation goal into account. That means, with striving for the same climate stabilization goal, the mitigation target is the more ambitious the larger the baseline emissions. This makes the mitigation under the SSP5 scenario more ambitious than under the SSP2 and even more than under the SSP1 scenario.

[4] The separation of equity and efficiency as well as the implied consequences holds under the assumption of perfectly competitive markets, but not necessarily in the presence of market power.

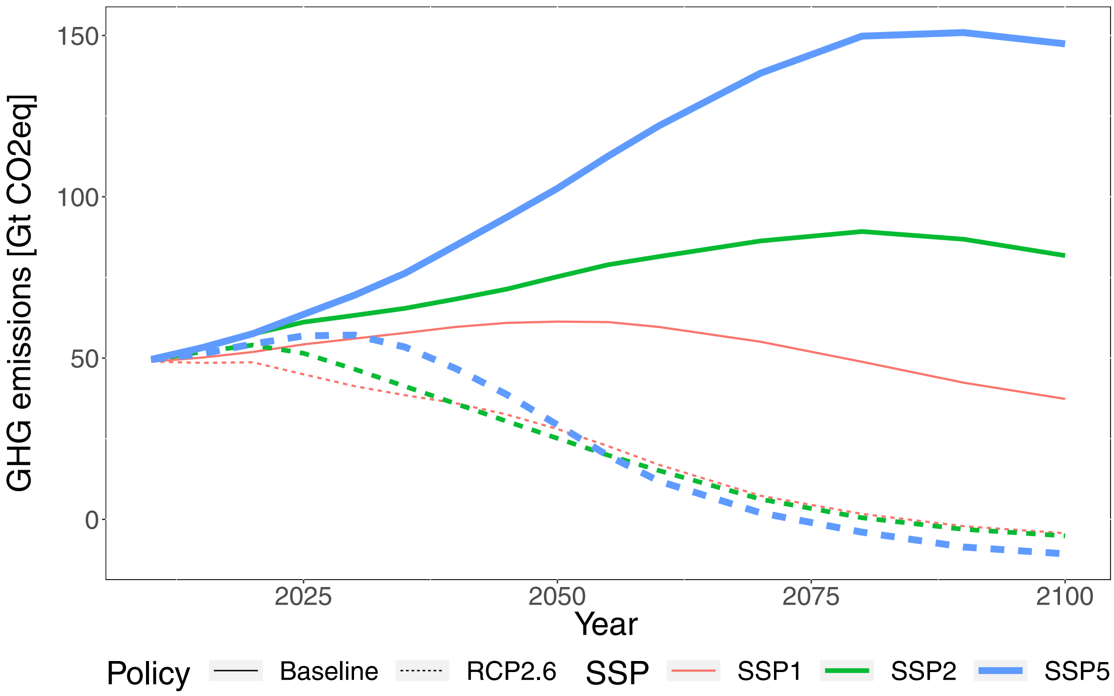

Fig. 1 Emission trajectories of baseline and RCP2.6 policy scenarios

If we compare the SSP2-TAX results with corresponding figures from IPCC's AR5 (IPCC 2014), we can summarize that the present analysis yields cost figures that are at the lower end of the respective IPCC range in the years 2030 (1%) and 2050 (2%) and close to the median in 2100 (5%).

5 Regional burden-sharing analysis

5.1 Allocation of mitigation efforts

In this subsection, we discuss the allocation of GHG emissions reductions needed to fill the mitigation gap identified in the previous section. The regional distribution of the related costs is discussed in the next subsection. To characterize the reduction efforts, we compare the emission level that each region is qualified for—from the allocation of allowances—with their actual emission level according to the globally cost-effective emission trajectory. From this comparison, we can conclude which regions face additional burden. Both variables represent share values measured as percentage amount of cumulated baseline emissions.

Whereas the allocation of allowances depends on the burden-sharing regime, the actual emission trajectories do not. We therefore start with analyzing the emission and emission reduction levels computed with the TAX scenarios. Cumulative regional reduction shares increase over time. Emission levels close to or below zero have to be achieved by most regions. As expected, SSP5 shows the highest shares in the long term. In the midterm, SSP2 demonstrates similar reduction shares (see Fig. 2). The maximum holds for AFR: up to 80% under SSP5 in 2100 compared with 65% in SSP2 and 60% in SSP1. Cumulative reduction shares differ more between regions for the time horizon until 2050 than until 2100. Figure 2 shows the cumulative emission reduction shares (until 2050) for each region across the three

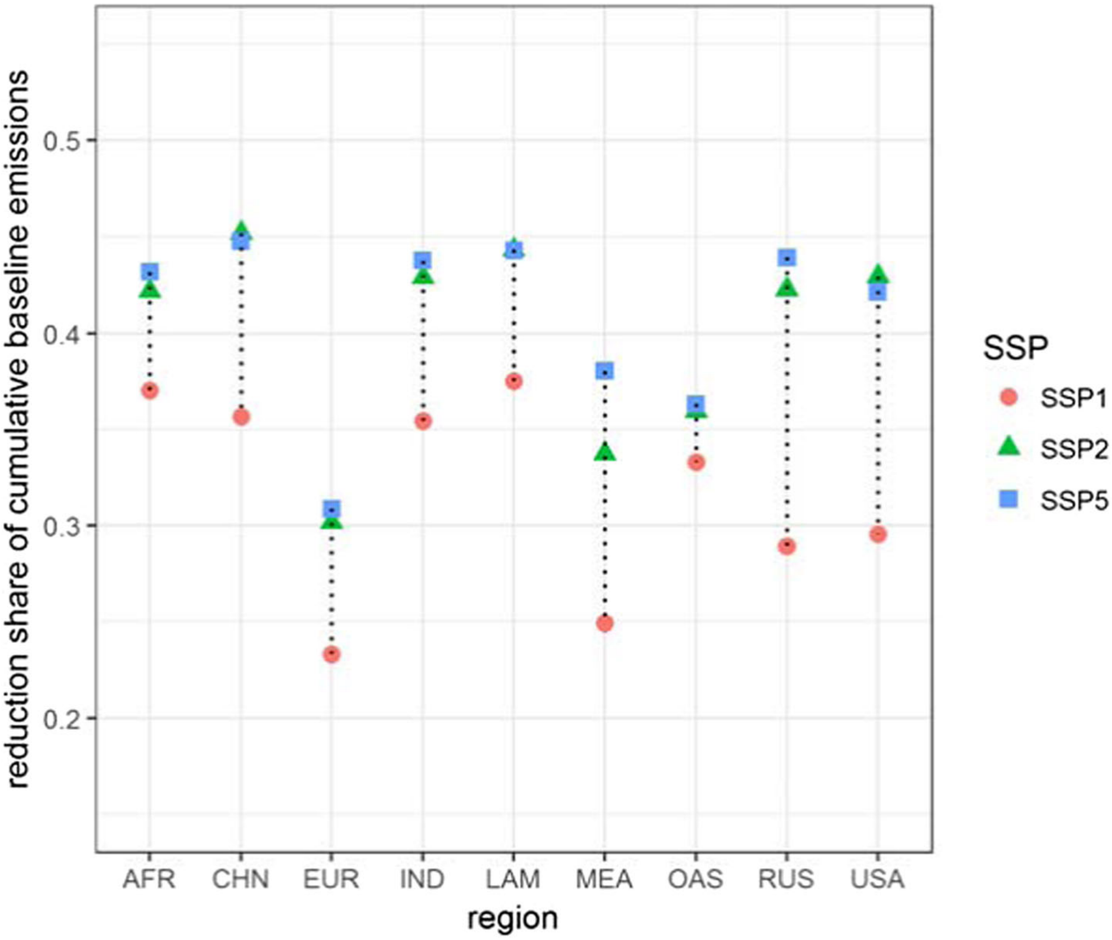

Fig. 2 Regional emission reduction shares cumulated over the time horizon 2015–2050

SSP scenarios.[5] Across all SSPs, developing regions (AFR, China, India, LAM) face the highest reduction shares. While higher reduction shares do not necessarily mean higher mitigation costs, fair burden-sharing schemes may have to take this reduction effort sharing into account.

The allocation of emission allowances varies only slightly across the different SSPs (see Fig. 3).[6] More remarkable is the variation of allocated allowances due to the different burden-sharing schemes. For nearly all regions, we can identify allocation schemes that provide permits in the range between 30 and 100% of baseline emissions. This range is, on the one hand, more narrow for China, LAM, and OAS, and on the other hand, expanded to values of well above 100% for AFR. The latter applies in the case of the equal effort-sharing regime also

[5] The share levels of SSP2 can be compared with those presented by Tavoni et al. (2015, Fig. 3). In the present study, share levels are in general slightly lower but show a higher spread between regions. In each of the two studies, EUR shows the lowest shares, which implies that the mitigation costs in this region increase faster with emission reductions than in other regions. It, moreover, indicates that the energy system in EUR today is more advanced and will not expand the use of fossil fuels within the near-term future as other regions will do in the baseline scenario.

[6] With the same stabilization target, and hence a similar global emission budget, the variation of the allocation of allowances across SSPs only depends on differences in the time profile of global emissions (see Fig. 1). In the short term, a higher (lower) absolute amount of permits is allocated under SSP5 (SSP1) than under SSP2. Since the respective baselines show the same differences, the allocation measured as aggregated share of baseline emissions shows low variance across SSPs.

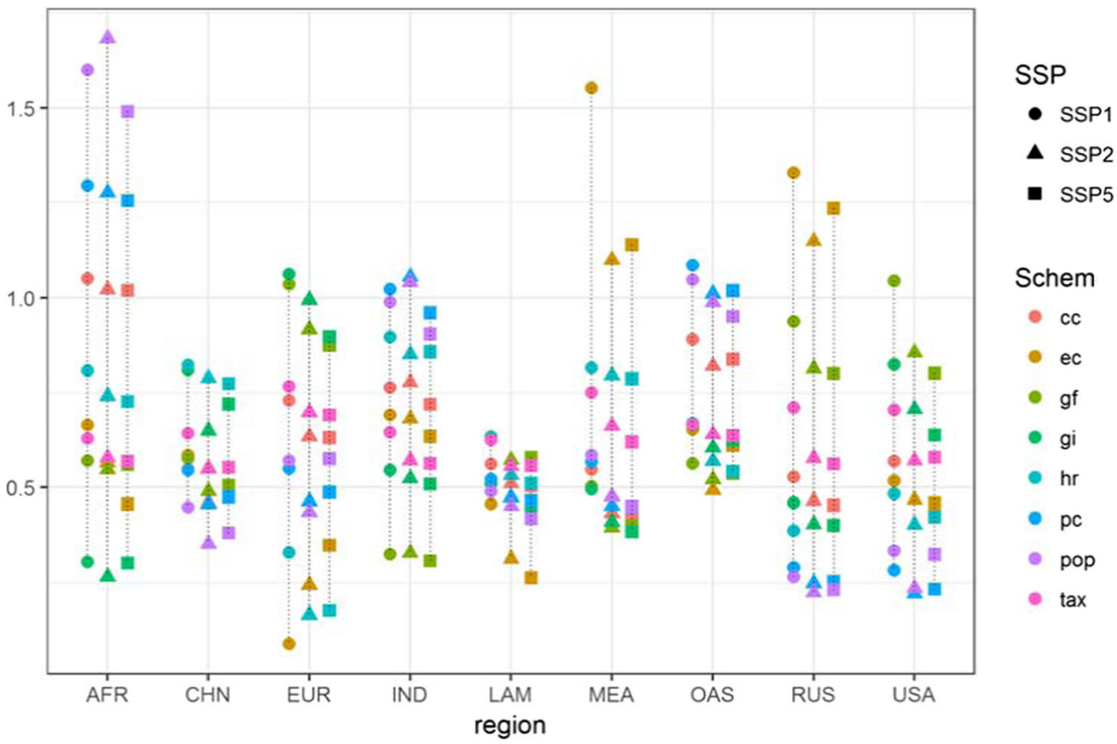

Fig. 3 Allocation of emission allowances per burden-sharing scheme measured as aggregated share of baseline emissions between 2015 and 2050

to MEA and Russia. Consequently, for each region, allocation schemes exist that provide either permits above or below the actual emission level. This reference level is represented in Fig. 3 by the pink "tax" marker. Whereas the actual emission level is at the upper part of the range of allocated allowances for LAM and for developed regions (the USA, EUR), it is more in the lower part for developing regions like AFR, India, and OAS. In the former case, additional expenditures on the carbon market are implied and in the latter case corresponding revenues. A further discussion on the advantages and disadvantages of the different burden-sharing regimes for each region will be provided in the context of the implied mitigation costs in the next section. A detailed time profile of respective permit allocations for each burden-sharing regime is shown in Fig. S.1 of the Supplementary Material.

5.2 Mitigation costs

When analyzing the regional mitigation costs, most integrated assessment studies apply results from tax scenarios only. Adding the SSP dimension, we find that the global ranking of SSPs in terms of mitigation costs also holds on the regional level (see Fig. 4). A notable exception is LAM for which we see lower costs in SSP5 than in SSP2 and SSP1. An explanation is given in Section 6 where a decomposition of the mitigation costs is presented. Despite the maintained ranking, we see that the SSP1 and SSP5 scenarios are relatively less costly for the developing countries than the SSP2 scenario. This is linked to the comparatively favorable demographic development (i.e., less population growth) and a higher degree of technological progress and diffusion in SSP1 and SSP5. While there are large differences in mitigation costs across countries and regions, each region's deviation from the global average, however, does not vary much across the different SSPs.

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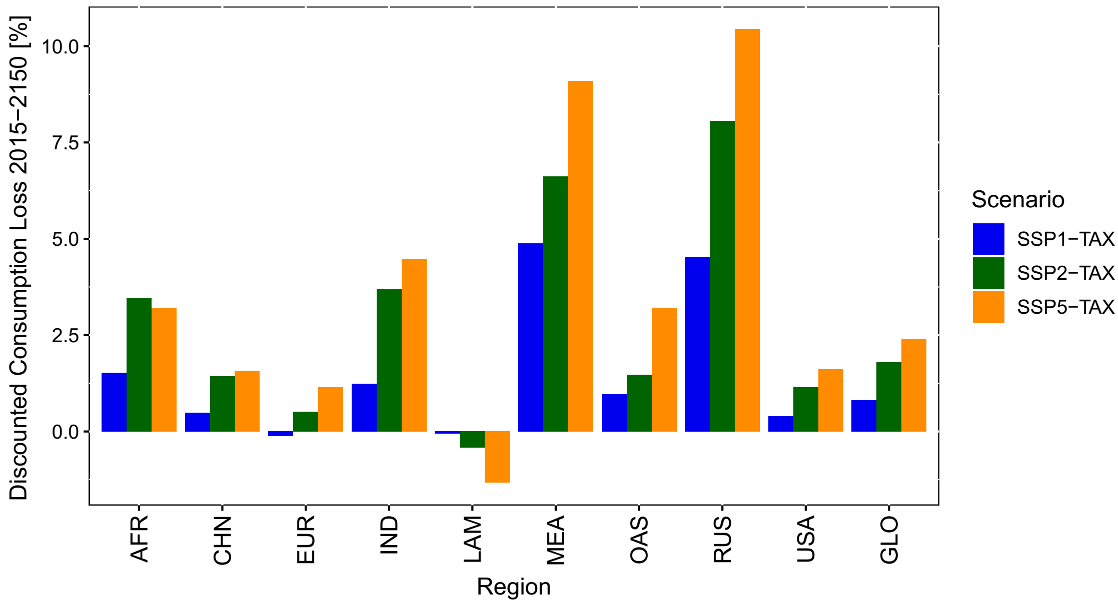

Fig. 4 Regional mitigation costs across the SSPs in ambitious climate stabilization scenarios (2.6 W/m^2) without climate finance

In the policy reference scenario (TAX), we see the highest mitigation costs for MEA and Russia than AFR and India. OAS, China, and the USA face mitigation costs around the global average or in the case of China and the USA partly even below the average. Finally, we observe the lowest costs for LAM and EUR. Apart from LAM, this ranking is the same as identified by Tavoni et al. (2015, Fig. 5) based on a multi-model comparison study of a policy scenario similar to the present SSP2-TAX scenario. Moreover, the level of mitigation costs of the SSP2-TAX scenario is also comparable with the results from the study by Aboumahboub et al. (2014, Fig. 1), except for China and Russia, for which we find lower mitigation costs.

The policy reference scenarios assume after an initial period of fragmented mitigation action a globally uniform carbon tax. While this ensures global efficiency, it disproportionately burdens less affluent countries. With introducing burden-sharing schemes that include climate finance based on an initial allocation of emission allowances, the distribution of mitigation costs (see Fig. 5) changes significantly. Non-equality-based burden-sharing regimes (e.g., GF, GI) increase the mitigation costs of developing regions like AFR and India substantially. For Russia and MEA, all burden-sharing regimes other than the equal effort-sharing (EC) yield mitigation costs well above the global average. The range of variation is rather small for the most developed regions EUR and the USA, which is mainly due to the fact that even comparably high expenditures on the carbon market represent a low share of consumption and GDP, respectively. Also for China and LAM, the variation is comparably low. Most extreme is the distribution of mitigation costs under the HR burden-sharing scheme. As the global mitigation costs are always the same across the burden-sharing schemes for a given climate target and a given SSP scenario, variation in the permit allocation always implies that some regions profit while others lose. The position of each region shows little variation across the SSPs. The implications of the PC and POP burden-sharing schemes in the case of India constitute a notable exception. While in SSP1 and SSP2, these burden-sharing regimes result in comparable low mitigation costs; they are well above the global average in SSP5. Due to higher economic growth in India in SSP5, that in the short-term is partly fueled by fossil

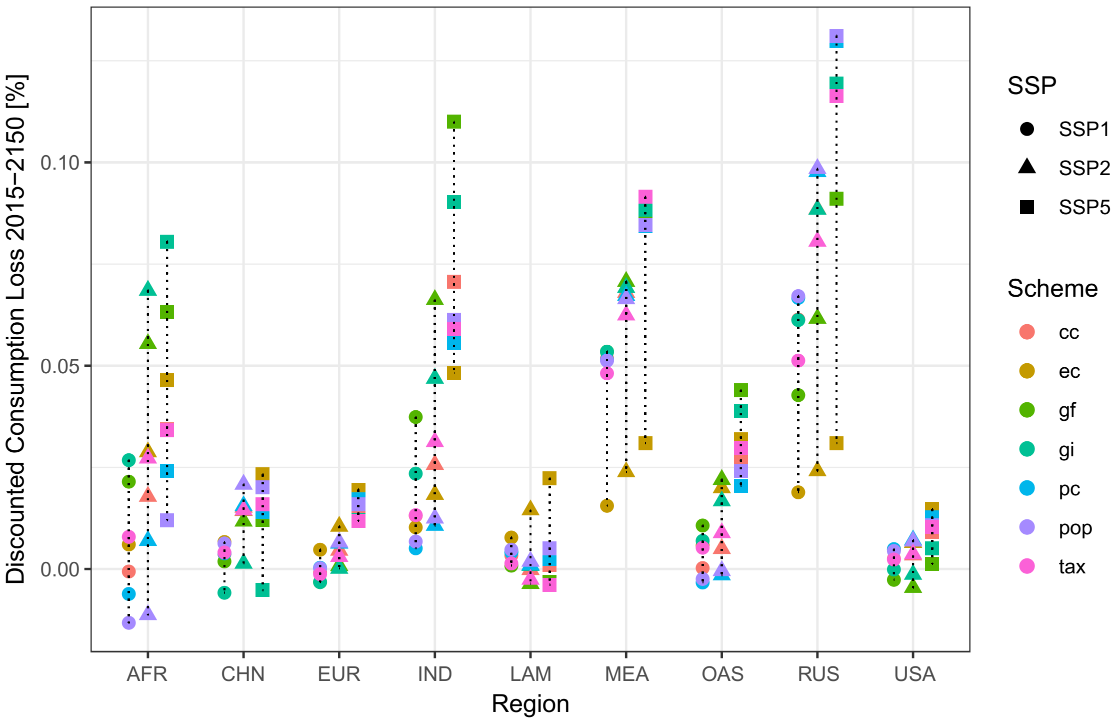

Fig. 5 Regional mitigation costs across the SSPs and burden-sharing regimes (we omit the HR scheme due to its extreme values for single regions)

resources, the domestic demand on emission permits increases and results in additional consumption losses that cannot be compensated by permit sales. Table S.1 in the Supplementary Material summarizes qualitatively the relative burden of each region under the different burden-sharing schemes.

5.3 Political feasibility of burden-sharing schemes

In the following, we aim for a further classification of the burden-sharing schemes. We assess their political feasibility measured by the implied amount of net transfers and the variation of regional mitigation costs.

The Supplementary Material (SM) illustrates and quantifies the cumulated permit trade value for each region, burden-sharing scheme, and SSP, until 2100 (Fig. S.2 and Table S.2). The transfer values show a wide range across the burden-sharing schemes for regions like AFR, EUR, and India, while they are narrower for Russia, LAM, and MEA if the EC regime is neglected. This can mainly be explained by the variation in the allocation of permits (see Fig. 3)—high variation for AFR, EUR, and India and low variation for LAM. For MEA and Russia, we observe large revenues from the permit market with the EC regime, but small trade volumes with all other regimes, due to the relative small scale of these economies. Figure 6a summarizes the total amount of transfers on the carbon market. It is the highest for the HR regime, comparatively high for the EC regime and the lowest for the CC regime. Across all burden-sharing regimes, we see the highest transfers for SSP5 and the lowest for SSP1, which implies that net transfers increase with the variation across regional mitigation costs. The spread, however, is not always equal. While the GF and GI regimes have a comparable amount of transfers as the PC and PI regimes under SSP1 and SSP2, it is substantially higher under

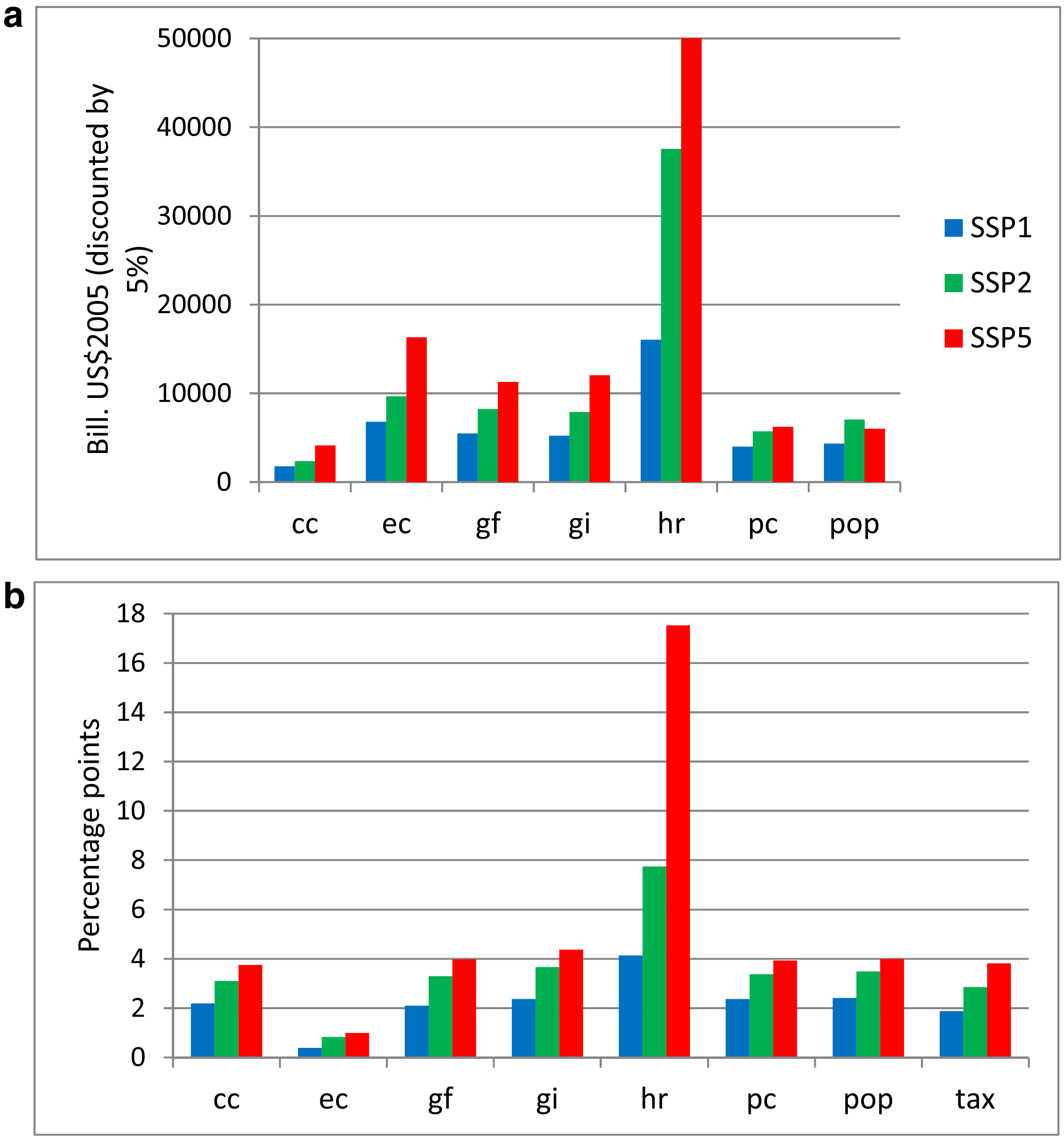

Fig. 6 Criteria of political infeasibility. **a** Global transfers on the carbon market until 2100. **b** Standard deviation of regional mitigation costs

SSP5. This is in particular due to the large increase of permit imports of AFR and India (and exports of China) under the GF and GI regime in SSP5 (see Fig. S.2).

With regard to the comparison of implied mitigation costs, we computed the standard deviation of mitigation costs—summarized in Fig. 6b. The contribution of permit trade to the mitigation costs in each region is presented in Table S.3 (SM). By construction, the EC regime demonstrates the lowest deviation of regional mitigation costs. Again, the highest levels are related to the HR regime. All other regimes demonstrate a similar standard deviation between 2 and 4 percentage points. These latter levels are comparable with the deviation of regional mitigation costs in the TAX scenarios. The ranking of mitigation cost levels across SSPs also holds for the standard deviation, with the highest figures for SSP5. While the increase of costs differences between SSP2 and SSP5 is in particular high for the HR regime, the PC and POP regimes see just a small difference between SSP2 and SSP5. In all burden-sharing regimes, apart from the EC and HR schemes, a substantial contribution to the standard deviation level is caused by high mitigation costs for MEA and Russia.

If we interpret high values in the two analyzed criteria (implied transfers and deviation in regional mitigation costs) as barriers of political feasibility, we come to the following conclusion. The regime based on historical responsibility is hardly feasible in the form implemented here, as it turns around the reduction burdens in an extreme way. Developed countries have to pay for the major part of global emission reduction despite of decreasing emission and population shares. Overall, the grandfathering and GDP intensity regimes—due to its higher amount of transfers—appear less feasible as the equality-based burden-sharing regimes, from which the contraction and convergence scheme has some additional merits due to a slightly lower implied transfer volume compared with the equal per capita and cumulated population share regime. The equal effort-sharing regime has a clear advantage with respect to one criterion but also a clear disadvantage with respect to the other. Compared with the burden-sharing scenarios with climate finance, the non-finance TAX scenarios (previous section) have a comparative advantage with respect to the two criteria assessed: no transfers at all and an average deviation of mitigation costs. Overall, the risk of political infeasibility increases clearly from SSP1 to SSP2 and to SSP5. A sustainable development as represented by the SSP1 scenario clearly reduces the challenges of burden sharing and makes it easier to achieve equitable climate policies.

At this point, we want to stress that we only analyzed pure allocation schemes—mixed types are possible and can potentially combine advantages. In addition, other evaluation criteria may shift the overall picture. In particular, the domestic dimension of distributional effects of climate policies is important, but not in the scope of this study.

6 Equality-based burden sharing

Equality-based burden-sharing regimes perform relatively well under the criteria considered in the previous section. In particular, they do not imply above average financial transfers as generally expected. We subject two of these schemes to an in-depth analysis: the per capita convergence (CC) and the population share (POP) burden-sharing schemes. This analysis provides findings that partly apply to other burden-sharing regimes as well and hence complements the analysis of Section 5.

Surprisingly, for most regions, mitigation cost differences are much higher between the two equality-based policy scenarios than between the corresponding TAX and CC scenarios (see Fig. 5). While mitigation costs for some of the most affected regions, namely, AFR and India, are high in the case of a global carbon tax and CC scenarios, they are low or even negative in the POP scenarios. In the POP scenarios, higher costs can be observed in particular in regions that feature according to the demographic projections less population growth or even a decline in population: China, EUR, and Russia. For the USA, under the POP scenario, there is hardly an increase of mitigation costs in SSP5 compared with the other SSPs. Because of higher population growth in SSP5, a larger amount of allocated emission permits benefits the USA.

Overall, there are large burdens on MEA and Russia. From a fairness perspective, this can be justified by the large benefits from fossil resource extraction in the past, which have only been possible due to ignorance of the external effects of fossil fuel consumption. Moreover, the large policy cost for MEA and Russia is heavily driven by a baseline that assumes a prolongation of the favor of non-internalizing external effects into the far future. Despite these

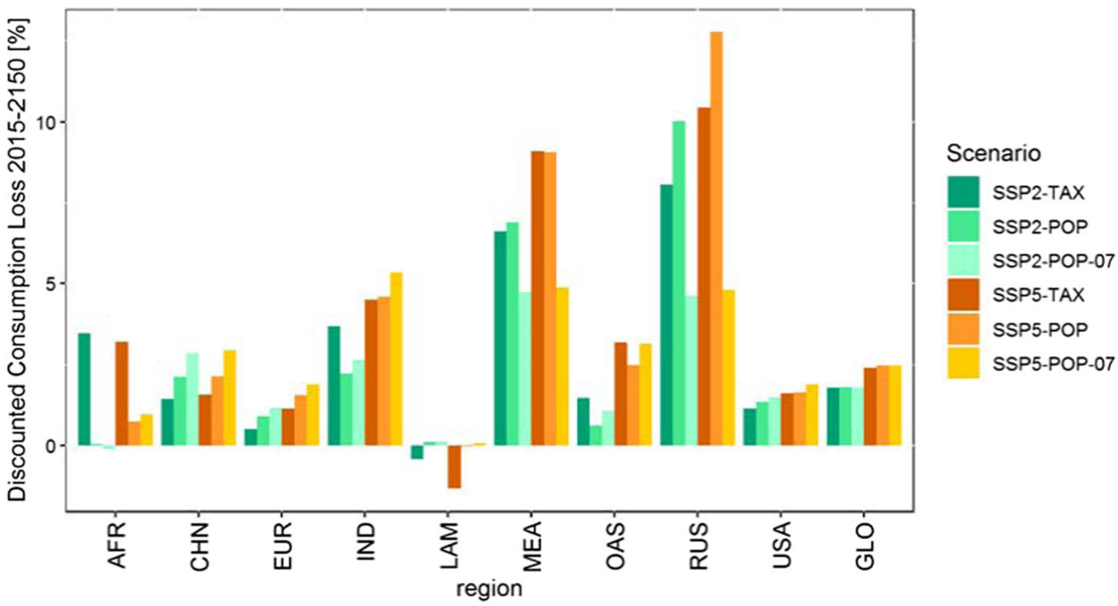

Fig. 7 Mitigation costs per region for the SSP2 and SSP5 in ambitious climate stabilization scenarios (2.6 W/m^2), including the 7% cost cap scenarios

arguments, a resistance of countries with large burden can be expected in climate policy negotiations. In order to reflect on this, we run an additional scenario ("POP-07") where the consumption losses compared with the baseline in each year are limited to a maximum of 7%. We chose this value in order to identify sensitivities of the interregional trade-offs. Beyond that, there is no other rationale behind this particular number.

The POP-07 scenario changes the burden sharing under SSP2 and in particular under SSP5 significantly (see Fig. 7). While the mitigation costs of Russia are more than halve in both SSP2 and SSP5, those of MEA are nearly halve in SSP5 and decrease by around 25% in SSP2. Mitigation costs increase in SSP2 and SSP5 by up to 0.3 and 0.5 percentage points, respectively, in other regions (China, India, EUR, the USA, OAS, LAM). In general, in all POP and CC scenarios, changes in the burden sharing (compared with the TAX scenario) result from indirect climate finance (i.e., endowment of emission permits). The POP-07 scenarios with a cost constraint imply an additional transfer. While the model computes this as a deficit in the intertemporal budget constraint (see the Supplementary Material A.6 for more details), in the real world, this can be any type of transfer, debt relief, and redistribution of carbon market revenues.

In the case of SSP2-POP-07, these additional transfers are largely compensated by transfers at the carbon market in the opposite direction. Hence, the total volume of net transfers only increases by few percentage points. In contrast, the SSP5-POP-07 scenario exhibits an increase of transfers by one-third compared with the respective SSP5-POP scenario. On the other hand, there is a significant decrease in terms of the deviation of regional mitigation costs. The standard deviation for both, the SSP2-POP-07 and SSP5-POP-07 scenario, is around 1.7% and thus more than halves compared with the respective POP scenarios (cf. Figure 6b). In case of SSP2, this result may be interpreted as an increase in political feasibility of the underlying burden-sharing regime.

In order to get additional insight into the differential impacts of SSPs on the regional mitigation costs, we perform a decomposition analysis. Details on this analysis are provided in the Supplementary Material (A.7). We identify components that contribute differently to the cost magnitude across regions and to the cost shares in regions across the SSPs. The slightly lower economic growth rates (Dellink et al. 2017) and the contained population growth (cf. KC and Lutz 2017) in SSP1 result in a somewhat lower contribution of GDP losses to the mitigation costs in SSP1, whereas energy system investments demonstrate a higher share in SSP1. First, this indicates that additional investments in carbon-free technologies are requested independently of the economic growth rate. Second, risk aversion on external environmental effects associated with large-scale biomass technologies (e.g., loss of biodiversity, reduction of food security) results in SSP1 in a preference to other forms of carbon-free energy technologies, like solar and wind, which have a higher fixed cost share than biomass technologies. Usage of biomass technologies in combination with carbon storage is in particular needed in SSP5 due to high fossil fuel use in the early years and is supported by less risk aversion to this technology compared with SSP1. In SSP5, biomass is used intensively as a liquid fuel and hence causes a price drop on the oil market that changes the contribution of oil and biomass trade to the mitigation costs substantially. The biomass trade effect is most pronounced for LAM. LAM is the major exporter of biomass and profits from a higher global demand for biomass and a price increase in SSP5. Consequently, LAM faces even lower mitigation costs in SSP5 than in SSP1 (cf. Figure 7).

The contribution of permit trade to the mitigation costs was already discussed in Section 5. Additional insights from the simulation of the CC and POP scenarios on the intertemporal dynamics of trade flows and transfer volumes are provided in the Supplementary Material (A.8).

7 Conclusions

This study quantifies the mitigation burden sharing of climate stabilization in different futures represented by the newly developed socio-economic pathways scenarios SSP1, SSP2, and SSP5. In accordance with what Riahi et al. (2017) already found, we identify the highest mitigation costs in SSP5 and the lowest in SSP1 at the global level. We show that this ranking also holds on the regional level. However, depending on the chosen burden-sharing scheme, mitigation costs can vary significantly across regions. Overall, the risk of political infeasibility of global burden-sharing regimes increases clearly from SSP1 to SSP2 and to SSP5, since the amount of net transfers increases as the variation across regional mitigation costs also does. This shows that a sustainable development pathway as represented by the SSP1 scenario reduces the challenges of burden sharing and makes it easier to achieve equitable climate policies.

By comparing different burden-sharing schemes with respect to criteria of political feasibility, we find that the equal effort-sharing scheme, while clearly distinguished by the balance of regional mitigation costs, has a disadvantage in the implied amount of net transfers. In contrast, the absence of any transfer implies a lower political challenge for non-climate finance scenarios like global tax scenarios. Yet, global tax scenarios disproportionately burden developing countries, which, in addition, will be affected by climate change impacts more heavily. Equality-based burden-sharing schemes perform quite well with respect to the criteria of political feasibility. They likely have an additional advantage regarding the fairness dimension that has not been quantified. By combination with a cost constraint, we demonstrate how the variation of regional mitigation costs in equality-based burden-sharing schemes could be decreased further. Under SSP2, this causes just a marginal increase of transfers and hence provides an alternative burden-sharing regime with a reasonable degree of political feasibility.

While this paper cannot provide final suggestions of how future climate policy regimes have to be designed, it nevertheless identifies burden-sharing implications of different socio-economic pathways that policy-makers should take into account. The burden-sharing perspective as well as the contributing components change with the SSPs and hence depend on how the world evolves. Further research will have to further deepen the understanding on this interrelation as well as add the perspective of the SSP3 and SSP4 pathways in this context.

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References

Aboumahboub T, Luderer G, Kriegler E, Leimbach M, Bauer N, Pehl M, Baumstark L (2014) On the regional distribution of climate mitigation costs: the impact of delayed cooperative action. Climate Change Economics 5:1440002

Berk MM, den Elzen MGJ (2001) Options for differentiation of future commitments in climate policy: how to realise timely participation to meet stringent climate goals? Clim Pol 1:465–480

Böhringer C, Helm C (2008) On the fair division of greenhouse gas abatement cost. Resour Energy Econ 30: 260–276

Coase RH (1960) The problem of social cost. J Law Econ 3:1–44

Dellink R, Chateau J, Lanzi E, Magne B (2017) Long-term growth projections in shared socioeconomic pathways. Glob Environ Chang 42:200–214

den Elzen MGJ, Lucas P, van Vuuren DP (2005) Abatement costs of post-Kyoto climate regimes. Energy Policy 33:2138–2151

den Elzen MGJ, van Vuuren DP, van Vliet J (2010) Postponing emission reductions from 2020 to 2030 increases climate risks and long-term costs. Clim Chang 99:313–320

Ekholm T, Soimakallio S, Moltmann S, Höhne N, Syri S, Savolainen I (2010) Effort sharing in ambitious, global climate change mitigation scenarios. Energy Policy 38:1797–1810

Gerlagh R (2007) The level and distribution of costs and benefits over generations of an emission stabilization program. Energy Econ 29:126–131

Herrala R, Goel RK (2016) Sharing the emission reduction burden in an uneven world. Energy Policy 94:29–39

Hof AF, den Elzen MGJ, van Vuuren DP (2010) Including adaptation costs and climate change damages in evaluating post-2012 burden sharing regimes. Mitig Adapt Strateg Glob Chang 15:19–40

Höhne N, Blum H, Fuglestvedt J et al (2011) Contribution of individual countries' emissions to climate change and their uncertainty. Clim Chang 106:359–391

Höhne N, den Elzen M, Escalante D (2014) Regional GHG reduction targets based on effort sharing: a comparison of studies. Clim Pol 14:122–147

IPCC (2014) Climate change 2014: mitigation of climate change. Contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change. http://www.ipcc.ch/report/ar5/wg3/

KC S, Lutz W (2017) The human core of the SSPs: population scenarios by age , sex and level of education for all countries to 2100. Glob Environ Chang 42:181–192

Klinsky S, Winkler H (2014) Equity, sustainable development and climate policy. Clim Pol 14:1–7

Kornek U, Steckel J, Lessmann K, Edenhofer O (2017) The climate rent curse: new challenges for burden sharing. Int Environ Agreements 17:855–882

Kriegler E, Edmonds J, Hallegatte S, Ebi KL, Kram T, Riahi K, Winkler H, van Vuuren DP (2014) A new scenario framework for climate change research: the concept of shared climate policy assumptions. Clim Chang 122:401–414

Kriegler E, Bauer N, Popp A, Humpenöder F, Leimbach M, Strefler J, Baumstark L et al (2017) Fossil-fueled development (SSP5): an energy and resource intensive scenario for the 21st century. Glob Environ Chang 42:297–315
Kriegler E, Bertram C, Kuramochi T et al (2018) Short term policies to keep the door open for Paris climate goals. Environ Res Lett 13:074022
Kverndokk S (1995) Tradeable CO_2 emission permits: initial distribution as a justice problem. Environ Values 4: 129–148
Kverndokk S (2018) Climate policies, distributional effects and transfers between rich and poor countries. Int Rev Environ Resour Econ 12:129–176
Lange A, Löschel A, Vogt C, Ziegler A (2010) On the self-interested use of equity in international climate negotiations. Eur Econ Rev 54:359–375
Leimbach M, Bauer N, Baumstark L, Edenhofer O (2010) Mitigation costs in a globalized world: climate policy analysis with REMIND-R. Environ Model Assess 15:155–173
Leimbach M, Roming N, Schultes A, Schwerhoff G (2018) Long-term development perspectives of Sub-Saharan Africa under climate policies. Ecol Econ 144:148–159
Luderer G, DeCian E, Hourcade J-C, Leimbach M, Waisman H, Edenhofer O (2012) On the regional distribution of mitigation costs in a global cap-and-trade regime. Clim Chang 114:59–78
Luderer G, Leimbach M, Bauer N, Kriegler E, Baumstark L, Bertram C, Giannousakis A, et al (2015) Description of the REMIND model (version 1.6). SSRN Scholarly Paper Rochester, NY: Social Science Research Network, November 30, 2015. https://papers.ssrn.com/abstract=2697070
Lüken M, Edenhofer O, Knopf B, Leimbach M, Luderer G, Bauer N (2011) The role of technological availability for the distributive impacts of climate change mitigation policy. Energy Policy 39:6030–6039
Manne AS, Stephan G (2005) Global climate change and the equity–efficiency puzzle. Energy 30:2525–2536
Marangoni G, Tavoni M, Bosetti V et al (2017) Sensitivity of projected long-term CO2 emissions across the shared socioeconomic pathways. Nat Clim Chang 7:114–117
Markandya A (2011) Equity and distributional implications of climate change. World Dev 39:1051–1060
MATCH (2017) Ad-hoc group for the modelling and assessment of contributions of climate change. Database, http://www.match-info.net
Mattoo A, Subramanian A (2012) Equity in climate change: an analytical review. World Dev 40:1083–1097
Metz B (2000) International equity in climate change policy. Integr Assess 1:111–126
Meyer A (2000) Contraction & convergence: the global solution to climate change. Schumacher Briefing No.5, Green Books Ltd., Foxhole
O'Neill BC, Kriegler E, Riahi K, Ebi KL, Hallegatte S, Carter TR, Mathur R, van Vuuren DP (2014) A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Clim Chang 122:387–400
Raupach MR, Davis SJ, Peters GP, Andrew RM, Canadell JG, Ciais P, Friedlingstein P, Jotzo F, van Vuuren DP, Le Qu C (2014) Sharing a quota on cumulative carbon emissions. Nat Clim Chang 4:873–879
Riahi K, van Vuuren DP, Kriegler E et al (2017) The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: an overview. Glob Environ Chang 42:153–168
Robiou du Pont Y, Jeffrey ML, Gütschow J, Roegelj J, Christoff P, Meinshausen M (2017) Equitable mitigation to achieve the Paris agreement goals. Nat Clim Chang 7:38–43
Rogelj J, Fricko O, Meinshausen M, Krey V, Zilliacus J, Riahi K (2017) Understanding the origin of Paris agreement emission uncertainties. Nat Commun 8:15748
Rose A, Stevens B (1993) The efficiency and equity of marketable permits for CO2 emissions. Resour Energy Econ 15:117–146
Rose A, Stevens B, Edmonds J, Wise M (1998) International equity and differentiation in global warming policy: an application to tradeable emission permits. Environ Resour Econ 12:25–51
Rose A, Wei D, Miller N, Vandyck T (2017) Equity, emissions allowance trading and the Paris agreement on climate change. Econ Dis Cli Cha 1:203–232
Tavoni M, Kriegler E, Riahi K, van Vuuren DP, Aboumahboub T, Bowen A, Calvin K et al (2015) Post-2020 climate agreements in the major economies assessed in the light of global models. Nat Clim Chang 5:119–126
UNFCCC (2015) Adoption of the Paris agreement. United Nations Framework Convention on Climate Change, Bonn
Vaillancourt K, Waaub J-P (2004) Equity in international greenhouse gases abatement scenarios: a multicriteria approach. Eur J Oper Res 153:489–505
Van den Berg NJ, van Soest HL, Hof AF, den Elzen MGJ, van Vuuren DP et al (2019) Implications of various effort-sharing approaches for national carbon budgets and emission pathways. Clim Chang. https://doi.org/10.1007/s10584-019-02368-y

Van Ruijven BJ, Weitzel M, den Elzen MGJ, Hof AF, van Vuuren DP, Peterson S, Narita D (2012) Emission allowances and mitigation costs of China and India resulting from different effort-sharing approaches. Energy Policy 46:116–134

Vrontisi Z, Luderer G, Saveyn B, Keramidas K, Lara AR et al (2018) Enhancing global climate ambition towards a 1.5°C stabilization: a short-term multi-model assessment. Environ Res Lett 13:044039

Yohe G, van Engel E (2004) Equity and sustainability over the next fifty years: an exercise in economic visioning. Environ Dev Sustain 6:393–413

Zhou P, Wang M (2016) Carbon dioxide emissions allocation: a review. Ecol Econ 125:47–59

5

Discussion and Outlook

5.1 Summary

In the current section, the principal insights of the main chapters of the thesis will be summarized. Overarching conclusions will be drawn in section 5.2.1, and the overall methodological approach will be discussed in 5.2.2, while future work and possible ways to address the limitations of the approaches used in the present thesis will be shown in section 5.3.

5.1.1 Economic Growth Uncertainty (Chapter 2)

Emission intensity targets are motivated by uncertainty
Based on the overview given in 1.1 we begin the summary with the single-region study on economic growth uncertainty. Baseline uncertainty is the term used to describe the incomplete information about future emissions due to lack of solid predictions of economic growth. It is one of the main motivations behind the adoption of emission intensity targets by some developing countries during the Paris process. Intensity targets—as opposed to absolute emission targets, i.e. reduction of emissions by an absolute amount—use metrics such as emissions per unit of Gross Domestic Product and are regarded as means to avoid the trade-off between high economic growth rates and climate protection. However, evidence exists suggesting the non-existence of this trade-off: on the one hand climate policy costs are found to be moderate in most studies, and on the other high economic growth rates can be sustained while carbon emissions are reduced.

Target sequencing matters in target choice
Further, intensity targets can become problematic in other ways, especially if a scenario of low growth materializes in which case the policy costs could rise drastically. Situations of sequential targets also do not seem to favor intensity targets in the case of climate change, as the long-term absolute target of "well below" 2 degrees warming is more easily achieved with intermediate targets of the same type. The reason behind the distortion appearing when in sequencing schemes targets of different types are mixed lies in the different expectations each target type generates for investors, potentially leading to economic disruptiveness with every target update. This analysis highlights a) the importance of explicitly accounting for socio-economic uncertainty and b) the advantage of absolute emission targets over intensity targets for the world's largest emitter, China.

5.1.2 Uncertainty in Techno-Economic Parameters (Chapter 3)

We now discuss uncertainty in techo-economic parameters in global scale. The cost of energy technologies constitutes an important component of the overall uncertainty present in mitigation pathways. More accessible energy conversion technologies (by means of lower capital costs or fuel extraction costs) decrease estimates for global mitigation costs. This, however, is true not only for the low-carbon options but for all the important energy supply technologies considered here. On the other hand, the need for emissions to reach net zero by mid-century remains unaffected by our consideration of uncertainty in the costs of energy technologies, this is seen by the year-of-carbon-neutrality which remains the same for almost all four hundred scenarios analyzed. The overall findings of the study are in line with previous studies highlighting the importance of negative emission technologies like biomass&CCS and energy intensity (in which the transport sector plays an important role, see below) in shaping climate mitigation pathways.

Economic sectors affected differently
The uncertainty in technology costs does not matter much in the power sector—where a multitude of options is available—but is decisive for the transport sector, where the substitutability is low and short-term emissions are predicted to keep rising even in deep decarbonisation scenarios. Back to the sustainability dimension, early action towards reducing emissions reduces the reliance on technologies with highly uncertain potential and with possible barriers in social acceptance, like bioenergy and carbon capture and storage, with moderate increase in total costs.

Response to increasing policy ambition
Different levels of climate policy stringency show different sensitivities in the costs and availability of energy technologies. In the no-policy baseline case, fossil fuels make up almost half of the effect that energy technology costs have on carbon emissions. Nuclear power also plays a role in the baseline and the continuation of the—unambitious—Paris pledges, but the effect of fossils (especially coal) and nuclear on emissions is dramatically reduced in the "well below 2 degrees" scenarios. Only the transport-related oil maintains some of its effect, as transport is the bottleneck sector (few options available compared to e.g. the power sector), while the costs of electric and hydrogen vehicles dominate all levels of policy stringency. Deep decarbonisation scenarios are also strongly affected by the availability of Carbon Capture and Storage, which is by far the technology with the highest impact on the carbon price level.

5.1.3 Socio-economic Uncertainty and Burden Sharing of Climate Change Mitigation (Chapter 4)

We finally shift the focus to the cooperative efforts of multiple regions towards climate stabilization. The economic efficiency of climate mitigation pathways under socio-economic uncertainty has been thoroughly investigated, but this is not the case for the important and necessary step that comes after efficiency, equity. Without equity consideration, future agreements on multilateral action against climate change will be at risk, as developing countries could argue on the basis of Shared but Differentiated Responsibilities and not sign agreements that not foresee a fair distribution of efforts towards climate stabilization. We examine the economic and policy implications of six burden sharing schemes under socio-economic uncertainty. The uncertainty scenarios are provided by the SSPs, while the burden sharing schemes follow different equity principles, e.g. capability, equality, responsibility, etc.

SSPs and global perspective
A world leaning towards sustainability—as, e.g. in a SSP1 scenario assuming a combination of resource efficiency, preferences for sustainable production methods and investment in human development—will distribute more easily the burden of climate stabilization between regions. The necessary inter-regional monetary transfers and the overall economic costs could be lower than in a world characterized by higher energy intensity and fossil resource use, as in a SSP5 scenario, thus increasing the equity of the burden sharing. However, as far as the regional mitigation costs is concerned, developing countries could face smaller increases in costs in an SS5 world due to slower population growth and higher degrees of technological progress.

Regional dynamics

In further detail, scenarios without climate finance are found to disproportionately burden less affluent countries. These scenarios feature carbon prices that are equal for all regions, regardless of the strength and status of their economy. This would have a completely different impact on e.g. India than in the EU. Even under consideration of climate finance scenarios, i.e. where regions face additional costs for obtaining emission allowances, richer regions are not expected to carry a rather higher burden because these additional costs represent a relatively small share of consumption and GDP. In terms of burden sharing schemes, the highest impact by a large margin is shown by a scheme that distributes emission allowances based on the contribution of each region to the current global warming (historical responsibility). Non equality-based burden sharing schemes, on the other hand, clearly provide a disadvantage for developing regions, as they increase their expenses in purchasing emission allowances. Equality-based burden sharing delivers a more moderate result than the one delivered by historical responsibility.

5.2 Conclusions

The conclusions are structured as follows: first the overall quantitative insights are discussed with a reference to the magnitude of the effect of uncertainty on mitigation, then more qualitative insights combining the findings of the three publications comprising the present thesis are given. Finally, the general modelling approach is assessed, followed with concluding remarks on the uncertainty analysis methods deployed throughout the work.

5.2.1 Overall conclusions

5.2.1.1 Magnitude of the effect of socio-economic uncertainty on climate mitigation pathways

Combining the results from the studies of the present thesis, we observe a considerable effect of socio-economic uncertainty on optimal climate mitigation pathways. Mitigation cost changes are found to be in the order of magnitude of doubling to tripling, depending on whether the underlying input parameter changes are from different SSPs, economic growth, or techno-economic scenarios. Also the ranges observed in emission scenarios are considerable, highlighting the need for careful consideration of socio-economic dynamics in analysis of future mitigation pathways. The common practice of sticking to the middle-of-the-road SSP2 scenario might be misleading.

5.2.1.2 Qualitative insights

Overall, the interaction between socio-economic uncertainty and the optimal design of policies for climate mitigation (globally and among world regions) is found to follow the sustainability dimension. This is found to hold also for scenarios without an equity consideration, i.e. without climate finance between world regions. Yet the direct link between sustainability and socio-economic uncertainty is enhanced when burden sharing schemes based on equality are considered. Further, under multiple criteria, which we divide in categories such as the environment, economic disruptiveness, economic efficiency, and expectation stabilization, economic growth uncertainty (main source of socio-economic uncertainty) is found to favor absolute emission reduction targets rather than the intensity targets (emissions per unit of GDP) adopted by developing countries.

Sustainability as described by the Share Socio-Economic Pathways (SSPs) is assisting climate mitigation, but targeted policies can eventually deliver quick results in sectors where these are needed. For example, a government support for lower prices of electric and hydrogen cars could lead to a substantial decrease in the overall climate mitigation costs. This is shown in our results and is further underpinned by the absence of flexibility in the transport sector.

5.2.2 Discussion

5.2.2.1 General modelling approach

The application of rich in detail energy-economy-climate models in the present thesis ensures that important path dependencies of the problem at hand are taken into consideration. Path dependencies are described as system configurations that respect the limitations dictated by past system states, e.g. due to existing investment lock-ins. A simple marginal abatement cost curve approach would not be sufficient as the metric that really matters is the so-called *levelized cost* of abated carbon, i.e. a metric that takes into consideration the business cycles of energy investment and effectively analyses the underlying trade-offs. Further, to achieve the necessary realism, advanced technologies like carbon capture and storage, bioenergy, synthetic fuels, electromobility, hydrogen, storage, and grid expansion need to be taken into account. The model REMIND has the ability to capture path dependencies, contains advanced techonoliges and features also the necessary tools for modeling carbon dioxide removal, which will play an important role in deep decarbonisation scenarios if the currently observed low-ambition policy is prolonged.

5.2.2.2 Modelling of climate policies

In terms of the model's ability to analyse different policy schemes, REMIND can be deployed in several modes, including cooperative and non-cooperative solutions, carbon price policy scenarios with and without climate finance, as well as in scenarios with emissions permit trading. This flexibility is needed for the possibility of considering a broad range of socio-economic futures.

5.2.2.3 Spatial flexibility and modelling of trade

Finally, the model is able to take into account different spatial resolutions, from single regions, like (China, India, the EU, etc.) to multi-region and global configurations. Trade of goods, energy resources, and emissions between regions is important for the economic accounting as well as the accounting in emissions, and is modelled in REMIND as well. The method used to model trade is based on a common-pool approach, with endogenously computed prices.

5.2.3 Suitability of used uncertainty analysis methods

5.2.3.1 Discrete Stochastic Programming

The application of methods for uncertainty analysis in the studies presented in this doctoral thesis illustrates possible ways to respond to the need for consideration of socio-economic uncertainty in energy- and climate change economics. The method of Discrete Stochastic Programming (DSP) that is used in the chapter on economic growth uncertainty (Chapter 2) involves a high computational burden and a large-scale algorithmic intervention in the REMIND model, but is the only method deriving a) a unique optimal path as response to the uncertainty and b) a hedging strategy, i.e. a strategy as response to uncertainty driven by the agent's risk aversion, and is consequently suitable for answering the research questions of which are the implications of economic growth uncertainty on climate policy and of which type of emissions target performs better under multiple criteria. DSP finally also allows for the consideration of learning* effects, which complete the uncertainty analysis.

5.2.3.2 Sensitivity analysis

To systematically analyze the effect of uncertainty in technology cost and availability on climate mitigation pathways (Chapter 3) the method of sensitivity analysis is used.

*Learning as additional information about uncertain parameters, not learning as it is defined when costs of technologies decrease with increasing installed capacity

Sensitivity analysis gives insights into a) the magnitude of the effect that different input parameters have on model outputs and b) the relative sensitivity of important model outputs in the inputs. These properties help quantify the effect and classify the important sources of uncertainty and potential bottlenecks in solution approaches (e.g. the transport sector and its lack of flexibility in technology switching).

5.2.3.3 Scenario analysis

The SSPs describe self-consistent storylines of human development and as such contain a plethora of parameters, like population, GDP, etc. To conduct an analysis using the SSPs as source of uncertainty (Chapter 4) the two previous methods are not suitable as they do not provide easy means for changing many input parameters at once. Scenario analysis is the suitable method in this case, as it involves the least computational effort and is widely used in most studies analyzing climate mitigation scenarios.

5.2.3.4 Regulatory uncertainty

In the introduction, we briefly examined the limitations of current modelling frameworks in addressing regulatory uncertainty. Quantifying the impact of regulatory uncertainty on the optimal response (hedging strategy) of energy investment paths demonstrates a potential limitation originating from the choice of modeling approach. It concretely shows that in a general equilibrium framework, the optimal risk strategy seen from the viewpoint of an investor can not be captured because of the fundamental assumption about the existence of a social-planner. A partial equilibrium model would be more adequate for capturing this effect. On the other hand, the hedging effect can be significant in the case of a different uncertain parameter such as the total economic output, because of the effect this parameter has on all factors of the production function. In any case, the effect of learning (i.e. updated information) about uncertainties remains significant, driven by the inertia of the system and the long-lived character of energy investment, which surpasses typical intervals of climate policy agreements and their announcements.

5.3 Future work

5.3.1 Overcoming limitations

The attractive property of delivering one single optimal path that takes into account all available uncertainty scenarios, featured by methods such as Discrete Stochastic Programming, comes with the limitation of considerable algorithmic and computational burden. It is, however, in some studies absolutely necessary for the sake of derivation of policy advice. Efforts towards improvement of models (especially integrated assessment models, which are very large in size) and methods aiming to achieve lower algorithmic and computational burden would enhance the quality of uncertainty analyses delivered. In a similar way, more efficient sampling methods for sensitivity analysis are being constantly developed and could be deployed with the constantly-increasing-in-size models frequenting climate change and energy economics studies. This would allow to explore methods beyond simple one-factor-at-a-time methods. Sensitivity analyses would ideally be delivered with *every* analysis published to help decision-makers better grasp the stakes involved.

Further, a more thorough analysis of important parameters to which models of climate change mitigation are found to be sensitive, like e.g. the pure time preference rate and the agent's risk aversion parameter, is needed to increase the robustness of model insights. Moreover, efforts in this direction have to be collective and take advantage of knowledge spillovers, in the sense that several models of the same type will have to contribute to this at the same time. In further steps, multi-objective analyses directly addressing trade-offs and synergies (such as environmental pollution and further Sustainable Development Goals), or new formulations of the model's objective functions (e.g. going beyond consumption maximization), could constitute great improvements of our modelling work.

5.3.2 Further topics

There are socio-economic factors that remain under-represented in uncertainty analyses. An example of this are additional options from the energy demand side, like heat-pumps and/or general consumer behavior, which could help complete the picture in the investigation of socio-economic uncertainty. Further, the impact of ongoing and future climate change on socio-economic scenarios describing the uncertainty space is necessary for better informing stakeholders and decision-makers. Efforts in this direction could greatly improve the usefulness of the SSPs.

A

A.1 Statement of Contribution

- Paper (Chapter 2): Anastasis Giannousakis, Lavinia Baumstark & Elmar Kriegler (2020) En route to China's mid- century climate goal: comparison of emissions intensity versus absolute targets, Climate Policy, 20:10, 1274-1289, DOI: 10.1080/14693062.2020.1798734

  All authors designed the research. Anastasis Giannousakis developed the stochastic model, did the model runs and the post-processing of the results, generated the plots, and wrote the paper. All authors read and commented on the paper, and agreed on the published version.

- Paper (Chapter 3): Anastasis Giannousakis, Jérôme Hilaire, Gregory F. Nemet, Gunnar Luderer, Robert C. Pietzcker, Renato Rodrigues, Lavinia Baumstark, Elmar Kriegler, "How uncertainty in technology costs and carbon dioxide removal availability affect climate mitigation pathways", Energy, Volume 216, 2021, 119253, ISSN 0360-5442, https://doi.org/10.1016/j.energy.2020.119253.

  Anastasis Giannousakis, designed the study, conducted the derivation of input data ranges, modeling work, post-processing, and created the figures, wrote the paper. Jérôme Hilaire supported the post- processing, and creation of figures, supported the derivation of input data ranges, wrote the paper. Gregory F. Nemet, designed the study, supported the writing. Gunnar Luderer, supported the derivation of input data ranges, supported the writing. Robert C. Pietzcker, supported the derivation of input data ranges, supported interpreting the results and deriving conclusions, supported the writing. Renato Rodrigues, supported the derivation of input data ranges, supported the writing. Lavinia Baumstark, supported the derivation of input data ranges. Elmar Kriegler, designed the study, supported the derivation of input data ranges. All authors have read and agreed to the published version of the manuscript.

- Paper (Chapter 4): Leimbach, M., Giannousakis, A. Burden sharing of climate change mitigation: global and regional challenges under shared socio-economic pathways. Climatic Change 155, 273–291 (2019). https://doi.org/10.1007/s10584-019-02469-8

  Marian Leimbach designed the research. Marian Leimbach and Anastasis Giannousakis produced the results and wrote the paper.

A.2 Chapter 2: Appendix

En route to China's mid-century climate goal: Comparison of emissions intensity versus absolute targets

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1. Supplementary Material

Appendix A.

Appendix A.1. The integrated assessment model REMIND

REMIND (REgional Model of INvestment and Development) is a multi-sector, multi-region integrated assessment model used for global and regional climate policy analysis (Luderer et al., 2015). REMIND has been used extensively in IPCC reports, e.g. IPCC (2014) and IPCC (2018), and major model intercomparison projects, e.g. Kriegler et al. (2014), Pietzcker et al. (2017), Bauer et al. (2018), Luderer et al. (2018), Riahi et al. (2017). It combines a top-down Ramsey-type growth model with a bottom-up energy system model of large technological detail. In the macro-economic core of REMIND, aggregated and discounted intertemporal social welfare is maximized for a number of regions spanning the whole globe, while pathways are derived for savings and investments, factor incomes, as well as energy and material demand. The utility function of REMIND exhibits constant relative risk aversion and has a logarithmic form on consumption. Regions interact by trade in primary energy carriers, emission permits, and a composite good. The detailed representation of the energy system in each region consists of capital stocks for more than 60 technologies for energy conversion, including technologies that are able to generate negative emissions, like bioenergy combined with carbon capture and sequestration.

In REMIND, economic activity results in demand for energy services, which in turn results in GHG emissions from extraction and burning of fossil fuels in different sectors (buildings, industry, transport) and levels (primary, secondary, and final energy). Mitigation scenarios analyze optimal strategies for decarbonization with the use of a carbon tax applied on the economy, resulting in a shift from fossil use to renewable energy. A full portfolio of GHG is considered (CO_2, CH_4, N_2O, NH_3, F-gases, etc.), either via emissions from energy use or via exogenous marginal abatement cost curves (e.g. land-use). Adjustment costs in energy investment and deployment account for policy realism and path dependency. REMIND usually runs in so-called cost-effectiveness mode, not internalizing potential economic damages of climate change, but rather analyzing energy technology portfolios and investment dynamics under given climate targets (GHG budgets, reduction relative to a baseline, carbon taxes, etc.)

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Appendix A.2. Decision-making under uncertainty in energy-economy models — Description of the REMIND-S model

There are several approaches in the literature to tackle uncertainty in climate policy analysis, reviewed extensively by Golub et al. (2014), Traeger (2009), Kann and Weyant (2000), Heal and Millner (2014), Heal and Kristrm (2002), Peterson (2005), and Baker and Shittu (2008). In energy-economy models, the first approach is called uncertainty propagation, and includes the methods of scenario analysis and sensitivity analysis. Although as methods they do not derive unique optimal decision paths, they provide important means for the design of climate policy. They do so by thoroughly exploring the scenario space and deriving detailed insights for each case, and by identifying which parameters contribute the most to uncertainty. A recent application of scenario analysis in the context of climate change are the SSPs (ONeill et al., 2014)), where self-consistent scenarios for the most important socio-economic drivers (population and economic growth, etc.) were developed for the future and a big body of studies was carried out shedding light on the implications of these socio-economic drivers for energy and land-use, emissions, climate change and mitigation of climate change (Riahi et al. (2017), Kriegler et al. (2017)). In other applications, Marangoni et al. (2017) use a sophisticated sensitivity analysis method to test various different parameters influencing emissions projections in the context of the SSPs, and conclude that economic growth and energy intensity are the most important drivers of uncertainty.

As a second approach to tackling uncertainty, methods performing decision-making under uncertainty are used. These include the methods of real option analysis (Anda et al., 2009) and stochastic modelling, e.g. discrete stochastic programming (Bosetti and Tavoni, 2009) and dynamic stochastic programming (Jensen and Traeger (2014) provide detailed estimates of optimal carbon taxes under long-term economic growth uncertainty using a dynamic stochastic integrated assessment model).

The model REMIND-S (REMIND-Stochastic) is presented here for the first time. It is the version of REMIND (see Appendix A.1) that explicitly accounts for uncertainty in one or more parameters. REMIND-S solves a Discrete Stochastic Programming (DSP) problem. DSP is a common method to explicitly account for uncertainty in integrated assessment models of climate change. It is widely used due to its moderate computational cost and useful insights, as well as the fact that it provides means for inclusion of stochasticity and multi-stage decision modelling. The key concept of DSP is to allow for the identification of one single optimal strategy under uncertainty (illustrated on the right panel of Fig. A.1), as opposed to multiple state-dependent optimal paths in a learn-then-act framework which can be explored by standard Monte Carlo, or simple deterministic scenario analysis (left panel of Fig. A.1). Thus, in DSP, the decision maker is exposed to a range of values of the uncertain parameter(s) in different "states-of-the-world" (realizations of the uncertain parameter), and still derives a single optimal path. The range of values of the uncertain parameter is described by a probability distribution running over the full set of states-of-the-world. This probability distribution can take any form and this is what gives the method the characterization "stochastic". REMIND-S features the exact same technological and sectoral detail as REMIND (the same holds for the rest of the model structure), but in REMIND-S expected utility is maximized, i.e. the weighted sum of utilities in each state-of-the-world, using the probabilities as weights, see equations describing the No-Learn and Act-Then-Learn cases in Fig. A.1. Thus, each state-of-the-world of REMIND-S is actually an instance of REMIND with different values for the uncertain parameters.

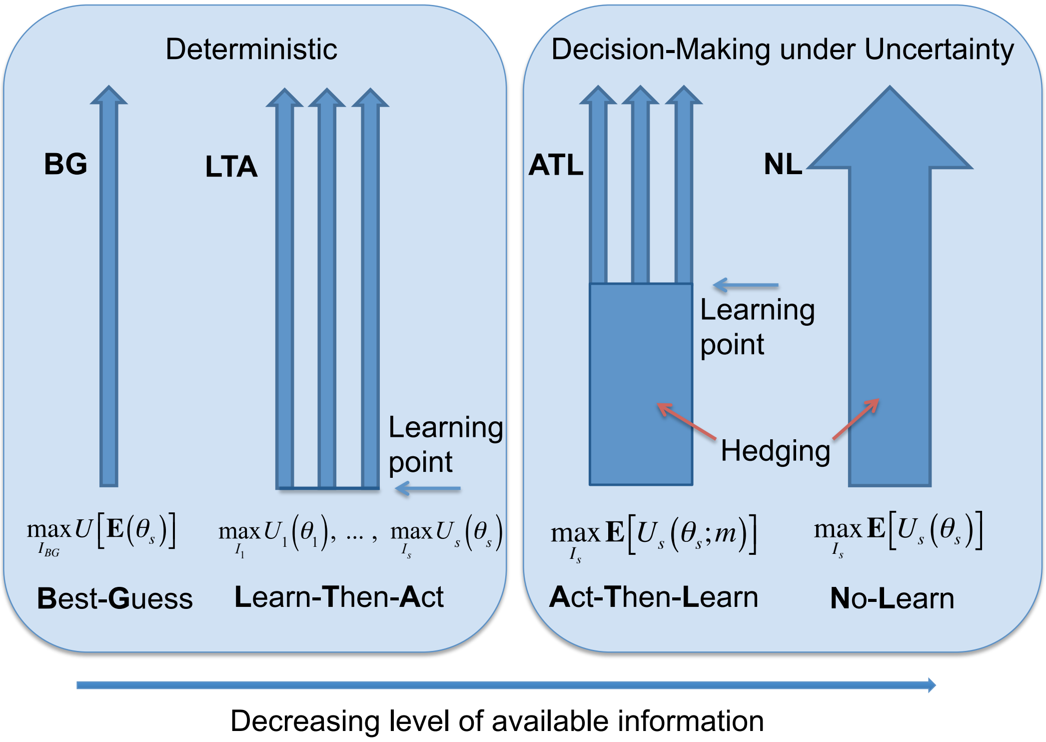

Figure A.1: Schematic representation of the various levels of uncertainty consideration applied here, and the respective objective functions. $\mathbf{E}$ is the expected value operator, U is the utility, s stands for state-of-the-world, I are the investment decisions, θ is the uncertain parameter, and m a message containing information about θ. "Learning" refers to the point in time where the message m is received. Hedging is defined as the decision path that responds to uncertainty, driven by the decision maker's risk aversion.

As mentioned above, the main feature of DSP is deriving a single optimal strategy under uncertainty. But capturing one single decision path poses a challenge in a complex model like REMIND-S, where various different investments and choices can be made. Thus, in REMIND-S, energy investments, fossil extraction rates and trade, as well as early retired capacity are equalized across the states-of-the-world using special constraints, which leads to equal emissions across the states-of-the-world; this is what is defined as one single optimal strategy. The presence of these constraints in an expected utility optimization framework gives rise to hedging strategies (the red arrows of Fig. A.1 show where the hedging takes place), as the best compromise between conflicting optimal decisions in each state-of-the-world is sought after. This happens before uncertainty is resolved (learning point of Fig. A.1), as the decision maker should be unaware of the state-of-the-world that will materialize. After the learning point the constraints are fully relaxed so that decisions can be tailored to individual growth scenarios, and emissions differ across the different states-of-the-world.

Risk aversion is described by the elasticity of intertemporal substitution (EIS), which describes also the decision maker's preference towards intertemporal equality, as we do not consider separate preferences (this would require a different type of modelling, as intertemporal optimization cannot be easily combined with separate preferences). In REMIND-S, EIS is equal to unity, giving the utility function its logarithmic form with diminishing returns of consumption, see Appendix A.1.

Appendix A.3. Uncertainty scenarios

A schematic of the approaches to uncertainty considered here is given in Figure A.1. First, in the presence of a symmetrical probability distribution, the medium growth or best-guess (BG) case is the situation where—given an uncertain parameter θ described by a known probability distribution—an optimal decision path can be derived under complete information using the best-guess value of θ, $\mathbf{E}(\theta)$, where $\mathbf{E}$ is the expected value operator. With "decision path" we refer to optimal energy planning configurations (i.e. investments, fuel extraction and trade, and capacity retirement decisions). The second case of Figure A.1, learn-then-act (LTA), describes a counterfactual, where uncertainty about θ is completely resolved before energy planning is performed, thus it can be fully adapted to each state-of-the-world (a "state-of-the-world" describes one realization of θ). Third, act-then-learn (ATL) is the case where all θ values remain possible and the decision path takes into account all of them at once. But the decision makers will eventually learn or be able to make better assumptions about the uncertain parameter; at a certain point in time uncertainty is resolved and the decisions after that point can be tailored to the individual messages received. Last, no-learn (NL) is a special case of ATL where learning never happens and decisions are taken under uncertainty throughout the time horizon.

Appendix A.4. How to hedge against growth uncertainty

Appendix A.4.1. Hedging in the absence of climate policy

Hedging is defined as the deviation of the single optimal decision path—produced with REMIND-S—when compared with the path of the deterministic case. But why does hedging appear in the first place, i.e. why is the single optimal path not simply the mean value between the growth scenarios (i.e. the medium growth—or best-guess—result in the case of a symmetrical probability distribution, like in this study)? The latter can be obtained by a simple scenario analysis, without stochasticity. In mathematical form (using the same notation as in Figure A.1):

$$\arg\max_{I} \mathbf{E}[U(\theta)] \quad \neq \quad \arg\max_{I_{BG}} U[\mathbf{E}(\theta)] \tag{A.1}$$

To answer this question we look into how uncertainty affects optimal investments. Uncertainty in economic growth leads to changes in optimal investment decisions already in the baseline case, in investments in the macroeconomic capital stock as well as energy investments. These changes occur while seeking one single energy investment path, i.e. the best compromise between all the possible growth scenarios (only one is allowed in REMIND-S because energy planning decisions cannot be tailored to individual growth scenarios prior to learning), when the decision maker necessarily ends up with a trajectory that lies somewhere between the optimal paths of the deterministic scenarios. This is the solution that includes the lowest sacrifice: the least possible overinvestment in case a low growth scenario realizes, the least possible underinvestment in case a high growth scenario realizes, and, if possible, neither overinvestment nor underinvestment in case the medium growth realizes. Indeed, as seen in Figure A.2 the overall result is an investment path (grey line) that lies between the High- and Low-growth scenarios, but lower than the medium growth path (black line), as the effect of uncertainty does not propagate linearly through the growth scenarios, see Equation A.1. More specific, if optimal investments were to lie above the medium growth case and a low growth scenario materialized, this suboptimality turns out to be more expensive than if the investments lie under the medium growth case, because in the high growth case the society is wealthier.

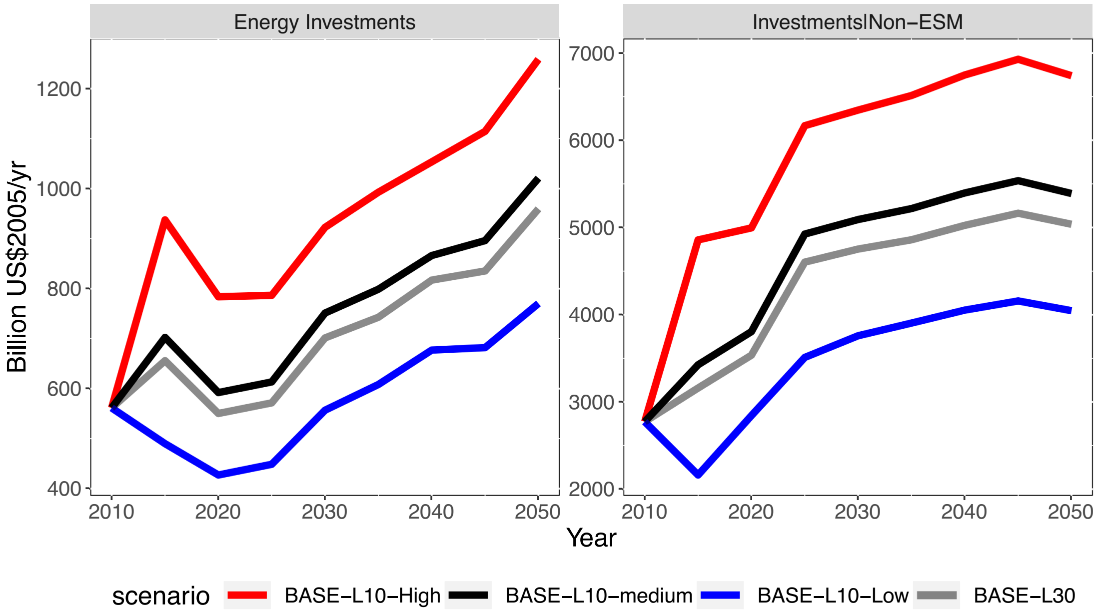

Figure A.2: Hedging in investments in the baseline case for China. Left: Energy investments. Right: Macro-economic investments. Note: macro-economic investments in the stochastic case are not equal across the growth scenarios, the grey line of the right graph describes the average. Energy investments are equalized in REMIND-S by definition.

Furthermore, as seen in Figure A.3, the percent reductions in optimal energy technology investments under uncertainty are not the same for each technology, showing a) energy-specific robust strategies in the baseline, and b) highlighting the necessity to use a technology-rich model for the present analysis.

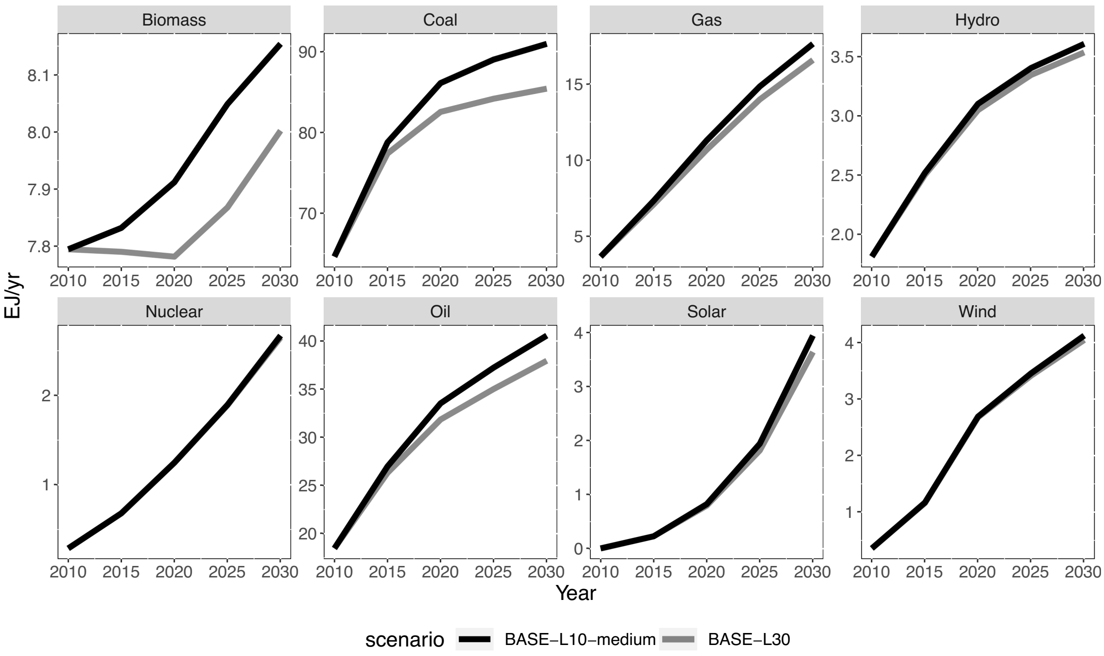

Figure A.3: Variation in the optimal use of key energy sources between the medium-growth/full-information and the BASE-L30 case (both without climate policy) in China. percent reduction is not the same for all energy types.

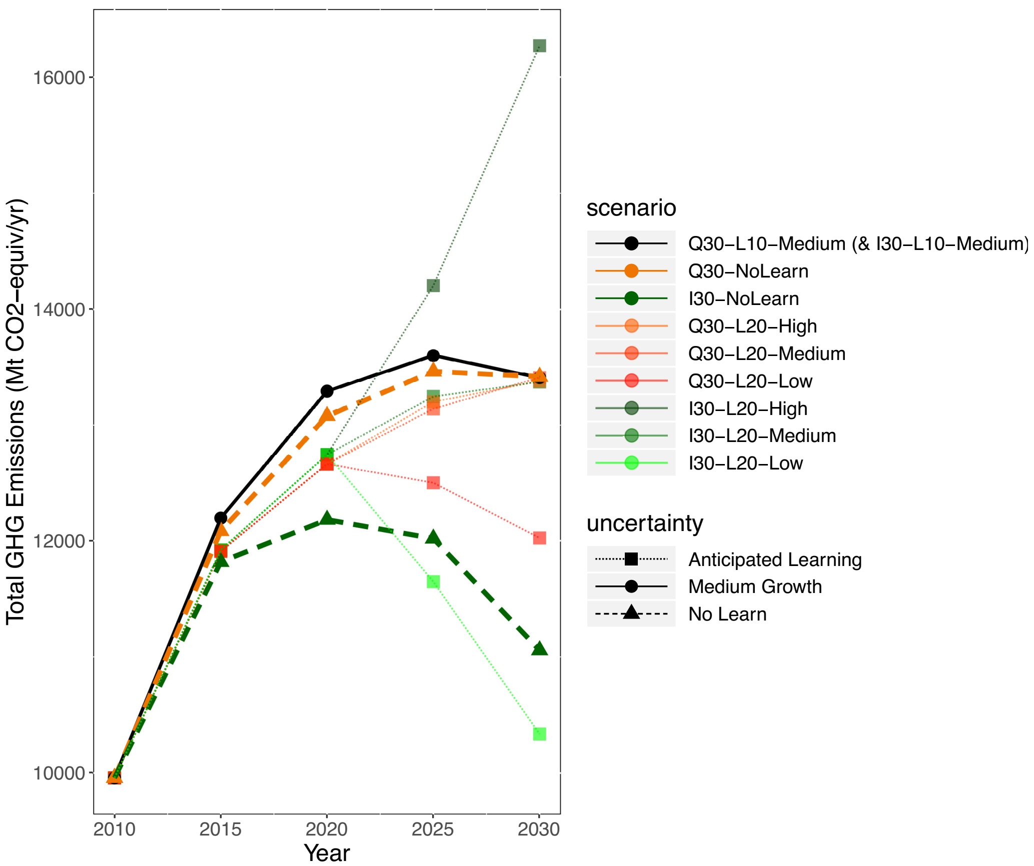

Figure A.4: Hedging (defined as the deviation from the medium-growth full-information line) in emissions in the scenarios with and without anticipated learning for stand-alone 2030 targets in China. Hedging is given by the difference between circles and triangles and is much stronger in the case of an intensity target (dark green vs. orange dashed lines), but is almost equalized when learning in 2020 is considered (squares in 2020). The separate paths after 2020 exist because energy planning can adapt to individual growth scenarios only after the learning point.

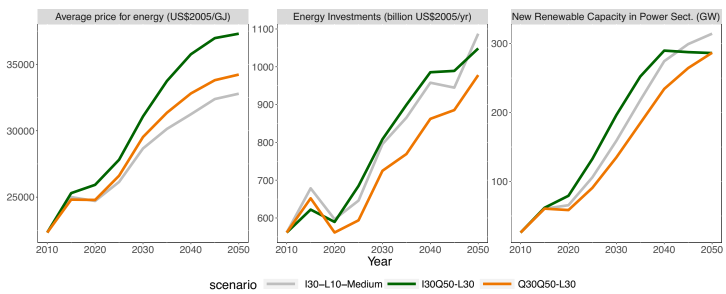

Figure A.5: Left: Energy is cheaper in the case of a quantity target in China, as a result of a wait-and-see strategy. Right: Optimal energy investments increase under uncertainty in the intensity target case, but decrease for a quantity target.

Appendix A.4.2. The effect of anticipated learning

When anticipated learning is considered (with a learning step in 2020, see A.4), more hedging (compared to the no-learn case) takes place in the quantity target scenario, as the available information after 2020 allows for the energy planner to respond to the upcoming target in 2030 individually, thus increasing investment and subsequently,

Table A.1: Effect of uncertainty and target type on welfare (expressed as percent changes in aggregate policy costs and measured in *certainty-equivalent balanced growth equivalents; CBGE*) for China: In the left column, a comparison of policy costs until 2030 between the deterministic and the scenarios with and without anticipated learning is shown. We see that anticipated learning about uncertainties increases welfare significantly (difference between Expected Value of Perfect Information; EVOPI, and Expected Value of Information; EVOI), and quantity targets can generate less costs than intensity targets. In the far right column, as reference, we show the corresponding climate policy costs until 2030, i.e. BASE-L30 vs. I30-L30 and Q30-L30, and baseline vs. policy with anticipated learning

	Target Type	EVOPI	Reference Costs
No-Learn	Quantity	3.16	0.62
	Intensity	4.1	1.6
		EVOI	
Anticipated Learning	Quantity	1.23	-0.06
	Intensity	1.32	-0.03

welfare, see Table A.1 (more on this in the next paragraph). All the Q30-L20 scenarios meet the 13.4 Gt target in 2030, except for the low growth scenario, where the target is not constraining, because overinvestment prior to the learning point combined with low growth result in a pathway with emission reductions stronger than what the target dictates. Overall, we see that learning eliminates to a great extend the difference between a quantity and intensity target. This is reflected also in the respective coal usage as seen in Figure A.6

The welfare losses due to uncertainty, measured in *certainty- and balanced-growth equivalents* (CBGE), sum up to 4.1 percent of net present value of total consumption, see Appendix A.5 for a detailed definition of the CBGE. This is called expected value of perfect information (EVOPI), and is reduced when learning is considered, as seen in Table A.1. The associated metric is called expected value of information (EVOI). This shows that with reduced uncertainty (learning), the target type choice plays less of an important role in the decision-making process.

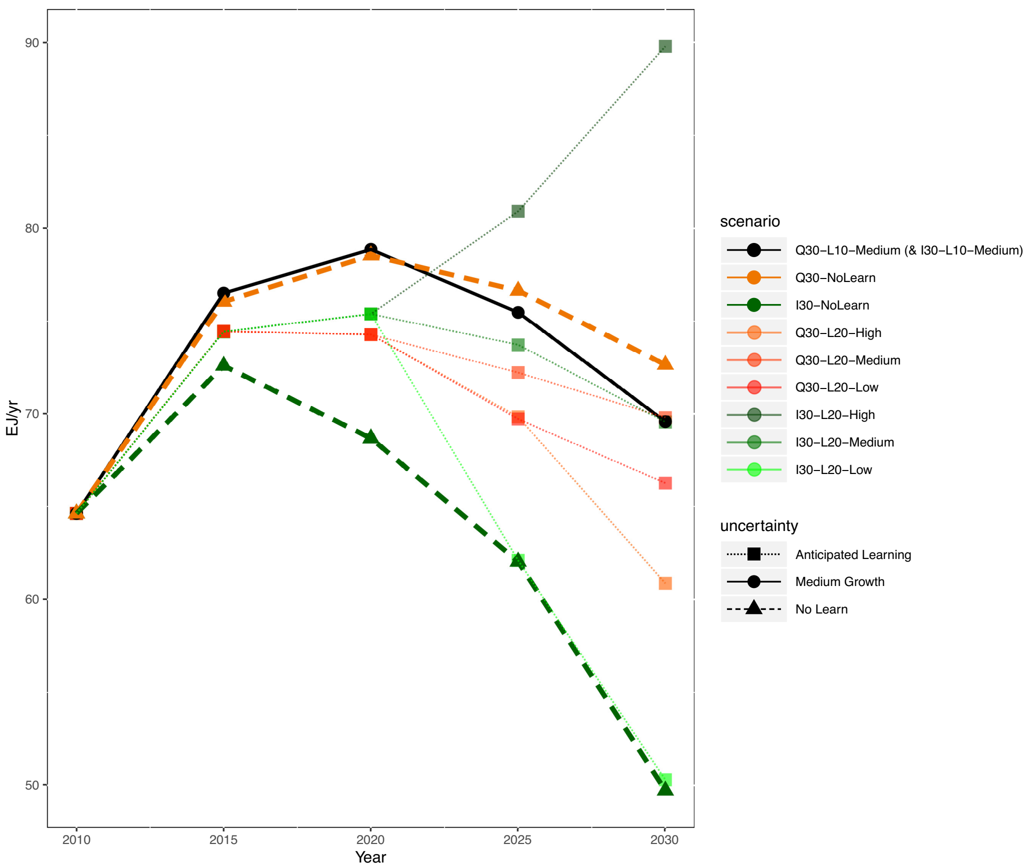

Figure A.6: Coal usage in China in the 2030 target case. The quantinty no-learn scenario features no decrease in coal consumption, compared to the deterministic medium-growth, but with anticipated learning (L20) coal is reduced. There is only one no-learn scenario for each target because all 3 scenarios have the same optimal energy planning, by definition (the same happens for the L20 scenarios prior to learning).

Appendix A.5. Policy costs measured in balanced growth equivalents

Climate policy costs in integrated assessment models are usually formulated in terms of relative differences in intertemporal, aggregated, and discounted consumption (or GDP) between cases with and without policy. When comparing climate policy costs across different baselines, as happens here where different growth scenarios are considered, this method of comparison fails to capture the welfare effects correctly, as for each case one ends up using a different yardstick. A measure that is more adequate is the *balanced growth equivalent* (BGE), which describes the amount of today's consumption, that, when extended into the future with a growth rate α, results in the same amount of utility U as the scenario in question. In mathematical form the BGE is the solution of the following equation with respect to γ:

$$\sum_{t=0}^{T} U[\gamma(\omega)(1+\alpha)^t]P_t(1+\rho)^{-t} = W(\omega) \tag{A.2}$$

where ω is the policy in question, P is population, t is the time and T the time horizon, ρ is the discount rate and W is the welfare. For a standard constant relative risk aversion utility function we get:

$$\gamma(\omega) = [(1-\eta)W(\omega)]^{\frac{1}{1-\eta}} \Big[\sum_{t=0}^{T} \frac{(1+\alpha)^{t(1-\eta)} P_t}{(1+\rho)^t} \Big]^{-\frac{1}{1-\eta}} \text{ , for } \eta \neq 0 \tag{A.3}$$

and

$$\gamma(\omega) = \exp\Big(\frac{W(\omega) - \ln(1+\alpha) \sum_{t=0}^{T} t P_t (1+\rho)^{-t}}{\sum_{t=0}^{T} P_t (1+\rho)^{-t}} \Big) \text{ , for } \eta = 0 \tag{A.4}$$

where η is the intertemporal elasticity of consumption.

Using the BGE relative differences between scenarios with different baselines are easily and intuitively comparable. For scenarios where expected utility is maximized the *certainty- and balanced-growth equivalent* is defined as the expected value of the BGE and used as adequate policy measure:

$$\text{CBGE} \equiv \mathbf{E}(\text{BGE}) = \sum_{i=1}^{s} \text{BGE}_i p_i \tag{A.5}$$

Appendix A.6. Sensitivity of policy costs on the growth of GDP

Here the results of a sensitivity analysis on the GDP growth rate in the deterministic case are presented (Table A.2).

Appendix A.7. Description of target rating criteria

We discuss the relative attractiveness of sequential intensity and quantity targets in terms of the criteria listed below (the respective categories are provided in brackets), based on the sequencing scenarios (Q30-L30 and I30-L30) of section 5.2. The expected value, i.e. the average between the three possible growth scenarios is taken for the calculation of all indicator values. The Q50-L10 medium-growth/full-information scenario—with which we normalize where noted—features full information about growth and 2050 target, and no 2030 target. For plots of the indicators see Figure 6. For a detailed view of the optimal paths in each growth scenario see Figure A.7.

GHG emissions [Environmental]

We describe the emissions indicator in terms of the total amount of GHG emissions emitted by each target type scenario in the period 2005-2050. The indicator is harmonized with the total GHG emissions reduction of the full-information scenario in the period 2005-2050.

Carbon price [Efficiency]

The size of the carbon price that has to be exerted on the economy for the target to be met. To account for time variability we take the net present value in 2020 (discounted at 5%) of the price path until 2050, and express the indicator as percentage of the medium-growth full-information case.

Welfare loss [Efficiency]

The welfare loss indicator measures which target features a smaller reduction of social welfare against the baseline in the period 2005-2050, relative to the reduction of the medium-growth full-information path (which thus has a value of 100%). We use BGE values in 2050 in order to account for baseline variability, see Appendix A.5.

Idle coal capacity [Disruptiveness]

Table A.2: Expansion of Table 2: Comparison of welfare effects until 2030 measured as percent changes in *balanced growth equivalents* (BGE, see Appendix A.5) for the different target types of the stand-alone 2030 scenarios. The GDP growth rate is increased gradually (in 10% steps) until the value that corresponds to the scenarios considered in our study in order to examine the sensitivity of policy costs to the GDP growth rate. The last two rows are the corresponding climate policy costs (i.e. comparison with the baseline) for each target and for the same period, which we use for reference.

Scenarios compared	**ΔBGE 2030 (%)**
High growth (I30-L10-High vs. Q30-L10-High)	1.00
High growth 90% (I30-L10-High vs. Q30-L10-High)	0.90
High growth 80% (I30-L10-High vs. Q30-L10-High)	0.82
High growth 70% (I30-L10-High vs. Q30-L10-High)	0.73
High growth 60% (I30-L10-High vs. Q30-L10-High)	0.67
High growth 50% (I30-L10-High vs. Q30-L10-High)	0.60
High growth 40% (I30-L10-High vs. Q30-L10-High)	0.48
High growth 30% (I30-L10-High vs. Q30-L10-High)	0.37
High growth 20% (I30-L10-High vs. Q30-L10-High)	0.25
High growth 10% (I30-L10-High vs. Q30-L10-High)	0.12
Medium growth (I30-L10-Medium vs. Q30-L10-Medium)	0
Low growth 10% (I30-L10-Low vs. Q30-L10-Low)	-0.09
Low growth 20% (I30-L10-Low vs. Q30-L10-Low)	-0.20
Low growth 30% (I30-L10-Low vs. Q30-L10-Low)	-0.27
Low growth 40% (I30-L10-Low vs. Q30-L10-Low)	-0.41
Low growth 50% (I30-L10-Low vs. Q30-L10-Low)	-0.55
Low growth 60% (I30-L10-Low vs. Q30-L10-Low)	-0.65
Low growth 70% (I30-L10-Low vs. Q30-L10-Low)	-0.75
Low growth 80% (I30-L10-Low vs. Q30-L10-Low)	-0.80
Low growth 90% (I30-L10-Low vs. Q30-L10-Low)	-0.90
Low growth (I30-L10-Low vs. Q30-L10-Low)	-0.97
Quantity (BASE-L10 vs. Q30-L10)	0.6
Intensity (BASE-L10 vs. I30-L10)	0.75

Expected retired coal capacity in the power sector (i.e. retired capacity that has not reached the end of its lifetime). To take into account also the years a power plant would spent in idle mode, we aggregate over time. The indicator is normalized with the medium-growth full-information scenario value.

Cost volatility [Disruptiveness]

The sequencing scenarios with unanticipated announcement of the 2050 target, exhibit a myopic behavior which can lead to jumps in costs. To capture these we calculate the difference in the carbon price across the various growth scenarios in the time before and after the target announcement (2030). Since each growth scenario has an independent carbon price, we take the expected value of the differences for each scenario in order to derive the cost volatility indicator.

Expected Value of Information [Expectation Stabilization]

Describes the value—in terms of welfare gains—of learning about growth uncertainty in 2030, i.e. it compares the BGE of the I30-L30 and Q30-L30 scenarios with the BGE of scenarios with no learning. See Table A.1 for more information on this indicator.

Non-optimal investment [Expectation Stabilization]

Acting under uncertainty necessarily leads to a suboptimal allocation of resources, as explained in section Appendix A.4. Thus, prior to the learning point, energy investment will be suboptimal. We measure this suboptimality by comparing the absolute difference between the net present value (with a discount rate of 5%) of the total energy investment of the period 2010-2030, i.e. up to the learning point, in the full-information case and each target scenario. Thus, medium-growth full-information has a zero value by definition, and we scale with the baseline value.

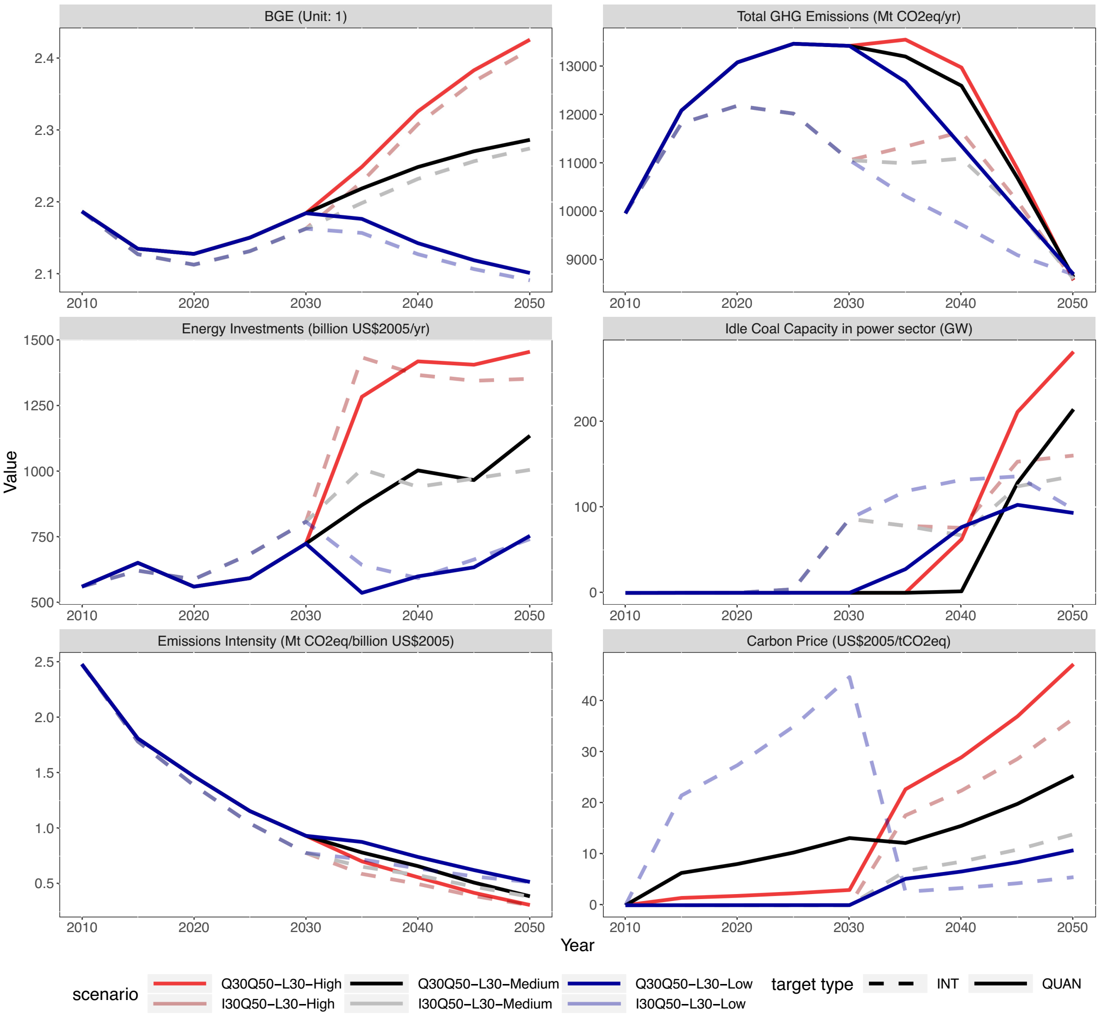

Figure A.7: Target sequencing scenarios for China: detailed view (with each growth scenario plotted separately) of the variables used for deriving the indicators for target comparison.

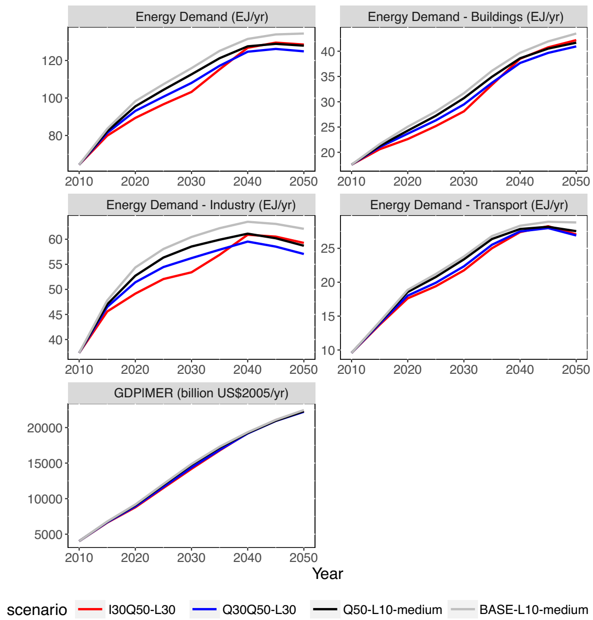

Figure A.8: Optimal paths of energy demand (total, and by sector) and GDP for the sequencing scenarios for China, under uncertainty. The graph shows how target sequencing shapes optimal emissions paths, plotted next to the hypothetical, full-information case of the 2 °C compatible stand-alone target in 2050—which we used to derive the optimal 2030 targets—and the counterfactual baseline scenario.

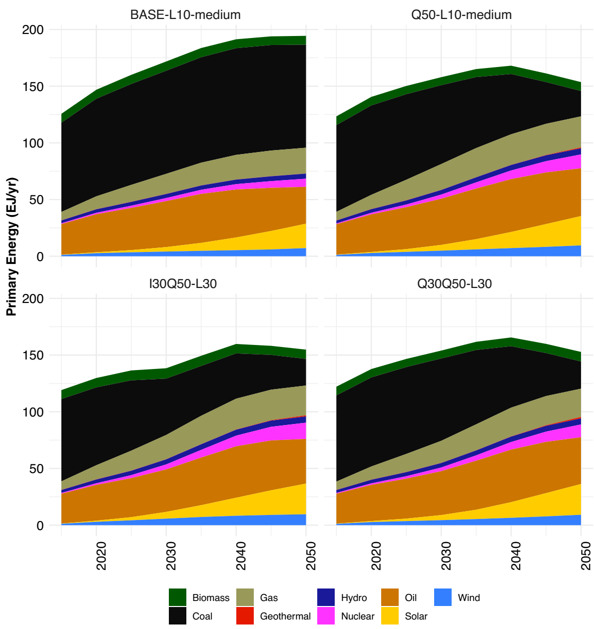

Figure A.9: Optimal energy mixes for the sequencing scenarios for China, under uncertainty. The graph shows how target sequencing shapes optimal emissions paths, plotted next to the hypothetical, full-information case of the 2 °C compatible stand-alone target in 2050—which we used to derive the optimal 2030 targets—and the counterfactual baseline scenario.

References

Anda, J., Golub, A., Strukova, E., 2009. Economics of climate change under uncertainty: Benefits of flexibility. Energy Policy 37, 1345–1355. URL: http://www.sciencedirect.com/science/article/pii/S0301421508007155, doi:10.1016/j.enpol.2008.11.034.

Baker, E., Shittu, E., 2008. Uncertainty and endogenous technical change in climate policy models. Energy Economics 30, 2817–2828. URL: http://www.sciencedirect.com/science/article/pii/S0140988307001211, doi:10.1016/j.eneco.2007.10.001.

Bauer, N., Rose, S.K., Fujimori, S., van Vuuren, D.P., Weyant, J., Wise, M., Cui, Y., Daioglou, V., Gidden, M.J., Kato, E., Kitous, A., Leblanc, F., Sands, R., Sano, F., Strefler, J., Tsutsui, J., Bibas, R., Fricko, O., Hasegawa, T., Klein, D., Kurosawa, A., Mima, S., Muratori, M., 2018. Global energy sector emission reductions and bioenergy use: overview of the bioenergy demand phase of the EMF-33 model comparison. Climatic Change URL: https://doi.org/10.1007/s10584-018-2226-y, doi:10.1007/s10584-018-2226-y.

Bosetti, V., Tavoni, M., 2009. Uncertain R&D, backstop technology and GHGs stabilization. Energy Economics 31, Supplement 1, S18–S26. URL: http://www.sciencedirect.com/science/article/pii/S0140988308000455, doi:10.1016/j.eneco.2008.03.002.

Golub, A., Narita, D., Schmidt, M.G.W., 2014. Uncertainty in Integrated Assessment Models of Climate Change: Alternative Analytical Approaches. Environmental Modeling & Assessment 19, 99–109. URL: http://link.springer.com/article/10.1007/s10666-013-9386-y, doi:10.1007/s10666-013-9386-y.

Heal, G., Kristrm, B., 2002. Uncertainty and Climate Change. Environmental and Resource Economics 22, 3–39. URL: https://link.springer.com/article/10.1023/A:1015556632097, doi:10.1023/A:1015556632097.

Heal, G., Millner, A., 2014. Uncertainty and Decision Making in Climate Change Economics. Review of Environmental Economics and Policy 8, 120–137. URL: https://academic.oup.com/reep/article/8/1/120/1590265/ReflectionsUncertainty-and-Decision-Making-in, doi:10.1093/reep/ret023.

IPCC, 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel of Climate Change. Technical Report.

IPCC, 2018. Global warming of 1.5C. An IPCC Special Report on the impacts of global warming of 1.5C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. Technical Report.

Jensen, S., Traeger, C.P., 2014. Optimal climate change mitigation under long-term growth uncertainty: Stochastic integrated assessment and analytic findings. European Economic Review 69, 104–125. URL: http://www.sciencedirect.com/science/article/pii/S0014292114000105, doi:10.1016/j.euroecorev.2014.01.008.

Kann, A., Weyant, J.P., 2000. Approaches for performing uncertainty analysis in large-scale energy/economic policy models. Environmental Modeling & Assessment 5, 29–46. URL: https://link.springer.com/article/10.1023/A:1019041023520, doi:10.1023/A:1019041023520.

Kriegler, E., Bauer, N., Popp, A., Humpender, F., Leimbach, M., Strefler, J., Baumstark, L., Bodirsky, B.L., Hilaire, J., Klein, D., Mouratiadou, I., Weindl, I., Bertram, C., Dietrich, J.P., Luderer, G., Pehl, M., Pietzcker, R., Piontek, F., Lotze-Campen, H., Biewald, A., Bonsch, M., Giannousakis, A., Kreidenweis, U., Mller, C., Rolinski, S., Schultes, A., Schwanitz, J., Stevanovic, M., Calvin, K., Emmerling, J., Fujimori, S., Edenhofer, O., 2017. Fossil-fueled development (SSP5): An energy and resource intensive scenario for the 21st century. Global Environmental Change 42, 297–315. URL: http://www.sciencedirect.com/science/article/pii/S0959378016300711, doi:10.1016/j.gloenvcha.2016.05.015.

Kriegler, E., Weyant, J.P., Blanford, G.J., Krey, V., Clarke, L., Edmonds, J., Fawcett, A., Luderer, G., Riahi, K., Richels, R., Rose, S.K., Tavoni, M., Vuuren, D.P.v., 2014. The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies. Climatic Change 123, 353–367. URL: http://link.springer.com/article/10.1007/s10584-013-0953-7, doi:10.1007/s10584-013-0953-7. 00138.

Luderer, G., Leimbach, M., Bauer, N., Kriegler, E., Baumstark, L., Bertram, C., Giannousakis, A., Hilaire, J., Klein, D., Levesque, A., Mouratiadou, I., Pehl, M., Pietzcker, R., Piontek, F., Roming, N., Schultes, A., Schwanitz, V.J., Strefler, J., 2015. Description of the REMIND Model (Version 1.6). SSRN Scholarly Paper ID 2697070. Social Science Research Network. Rochester, NY. URL: https://papers.ssrn.com/abstract=2697070.

Luderer, G., Vrontisi, Z., Bertram, C., Edelenbosch, O.Y., Pietzcker, R.C., Rogelj, J., Boer, H.S.D., Drouet, L., Emmerling, J., Fricko, O., Fujimori, S., Havlk, P., Iyer, G., Keramidas, K., Kitous, A., Pehl, M., Krey, V., Riahi, K., Saveyn, B., Tavoni, M., Vuuren, D.P.V., Kriegler, E., 2018. Residual fossil CO 2 emissions in 1.52 C pathways. Nature Climate Change 8, 626. URL: https://www.nature.com/articles/s41558-018-0198-6, doi:10.1038/s41558-018-0198-6.

Marangoni, G., Tavoni, M., Bosetti, V., Borgonovo, E., Capros, P., Fricko, O., Gernaat, D.E.H.J., Guivarch, C., Havlik, P., Huppmann, D., Johnson, N., Karkatsoulis, P., Keppo, I., Krey, V., Broin, E., Price, J., van Vuuren, D.P., 2017. Sensitivity of projected long-term CO2 emissions across the Shared Socioeconomic Pathways. Nature Climate Change advance online publication. URL: http://www.nature.com/nclimate/journal/vaop/ncurrent/full/nclimate3199.html, doi:10.1038/nclimate3199. 00000.

ONeill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., Vuuren, D.P.v., 2014. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Climatic Change 122, 387–400. URL: http://link.springer.com/article/10.1007/s10584-013-0905-2, doi:10.1007/s10584-013-0905-2.

Peterson, S., 2005. Uncertainty and economic analysis of climate change: A survey of approaches and findings. Environmental Modeling & Assessment 11, 1–17. URL: http://link.springer.com/article/10.1007/s10666-005-9014-6, doi:10.1007/s10666-005-9014-6.

Pietzcker, R.C., Ueckerdt, F., Carrara, S., de Boer, H.S., Desprs, J., Fujimori, S., Johnson, N., Kitous, A., Scholz, Y., Sullivan, P., Luderer, G., 2017. System integration of wind and solar power in integrated assessment models: A cross-model evaluation of new approaches. Energy Economics 64, 583–599. URL: http://www.sciencedirect.com/science/article/pii/S0140988316303395, doi:10.1016/j.eneco.2016.11.018.

Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., ONeill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J.C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpender, F., Da Silva, L.A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., Tavoni, M., 2017. The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Global Environmental Change 42, 153–168. URL: http://www.sciencedirect.com/science/article/pii/S0959378016300681, doi:10.1016/j.gloenvcha.2016.05.009.

Traeger, C.P., 2009. Recent Developments in the Intertemporal Modeling of Uncertainty. Annual Review of Resource Economics 1, 261–286. URL: http://dx.doi.org/10.1146/annurev.resource.050708.144242, doi:10.1146/annurev.resource.050708.144242.

A.3 Chapter 4: Appendix

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Burden Sharing of Climate Change Mitigation: Global and Regional Challenges under Shared Socio-Economic Pathways

Supplementary Material

Marian Leimbach, Anastasis Giannousakis

A.1 The integrated assessment model REMIND

REMIND is a global, multi-regional, energy-economy-climate model used in long-term analyses of climate change mitigation (e.g. Leimbach et al., 2010, Bauer et al., 2012, Bertram et al., 2015). A detailed model description is provided by Luderer et al. (2015).

The macro-economic core of REMIND is a Ramsey-type optimal growth model in which intertemporal global welfare is maximized. The model computes a unique Pareto-optimal solution that corresponds to the market equilibrium in the absence of non-internalized externalities. The world is divided into eleven model regions: Sub-Saharan Africa (AFR), China, EU-28 (EUR), India, Japan, Latin America (LAM), Middle East and North Africa (MEA), Other Asia (OAS), Russia, USA and Rest of the World (ROW). Model regions trade final goods, primary energy carriers, and in the case of climate policy, emissions permits. Macro-economic production factors are capital, labor, and final energy.

Economic activity results in demand for different types of final energy (electricity, solids, liquids, gases, etc.), determined by a production function with constant elasticity of substitution, and differentiated by stationary and transport uses. The energy system accounts for regional exhaustible primary energy resources through extraction cost curves. Bioenergy comes from different feedstocks: traditional biomass and first generation biomass, both assumed to phase out in the near future, as well as ligno-cellulosic residues and purpose-grown second-generation biomass. The regional biomass potential is represented by regional supply curves (Klein et al., 2014), which are derived from the land use model MAgPIE (Lotze-Campen et al., 2008). Costs of biomass production hence include opportunity costs of alternative land uses, e.g. using land for food production. Non-biomass renewable energy potentials are reflected in detail on the regional level. More than 50 technologies are available for the conversion of primary energy into secondary energy carriers as well as for the distribution of secondary energy carriers into final energy. Techno-economic parameters (investment costs, operation and maintenance costs, fuel costs, conversion efficiency etc.) characterize each conversion technology.

The model accounts for carbon dioxide emissions from fossil fuel combustion and land use as well as emissions of other greenhouse gases (GHGs). The climate model MAGICC6 (Meinshausen et al., 2011), which emulates more complex general circulation models, is used to translate emissions into changes of atmospheric GHG concentrations, radiative forcing, and global mean temperature.

A.2 Equal effort sharing

In the burden sharing regime with equal effort sharing, regions face the same, i.e. global average, consumption losses per GDP (or consumption, alternatively) at each point in time:

$$\frac{CL_r}{GP_r} = \frac{CL_{glob}}{GP_{glob}} = CL^0 \qquad \forall\ r = 1, ..n$$

Applying eq. (1) as strict equation we get

$$DC_r + CTC_r = GP_r * CL^0$$

Applying eqs. (2) and (3) it holds

$$p\left(S_r \sum_{r=1}^{n} E_r - E_r\right) = DC_r - GP_r * CL^0$$

From that we can derive the regional permit emission share

$$S_r = \frac{E_r + \frac{DC_r - CL_{glob}\frac{GP_r}{GP_{glob}}}{p}}{\sum_{r=1}^{n} E_r}\ .$$

A.3 Historic responsibility

With baseline and policy emissions E^{BAU} and E^{pol}, and the contribution SHR of each region to the temperature increase until 2005, we compute the regional permit emission share associated with the burden sharing according to the historic responsibility by

$$S_r = \frac{E_r^{BAU} - SHR_r \cdot \sum_{r=1}^{n}\left(E_r^{BAU} - E_r^{pol}\right)}{\sum_{r=1}^{n} E_r^{pol}}\ .$$

A.4 Ex-post analysis

Based on the separation of efficiency and equity, the mitigation costs (percentage consumption losses, CL) can be represented by two parts – the domestic costs DC (mainly costs of energy system transformation) and carbon trade cost CTC (see Luderer et al., 2012):

$$CL \approx DC + CTC \qquad (1)$$

In common tax scenarios the second part vanishes. In cap-and-trade scenarios, the second part is different from zero and can be computed for each region r as a product of the global carbon price (p) and the permit trade volume (PT):

$$CTC_r = p \cdot PT_r \qquad (2)$$

This trade volume can be calculated as the difference between the allocated permits (with S as allocated share) and the actual regional level of emissions E:

$$PT_r = E_r - S_r \bullet \sum_r E_r \qquad (3)$$

The needed input for this ex-post-analysis (i.e. data on global carbon price, global and regional GHG emissions) is derived from REMIND mitigation scenarios SSPx-TAX as introduced in section 3. The remaining unknown variable, the allocated share *S*, is provided by different burden sharing schemes.

A.5 Results from ex-post analysis

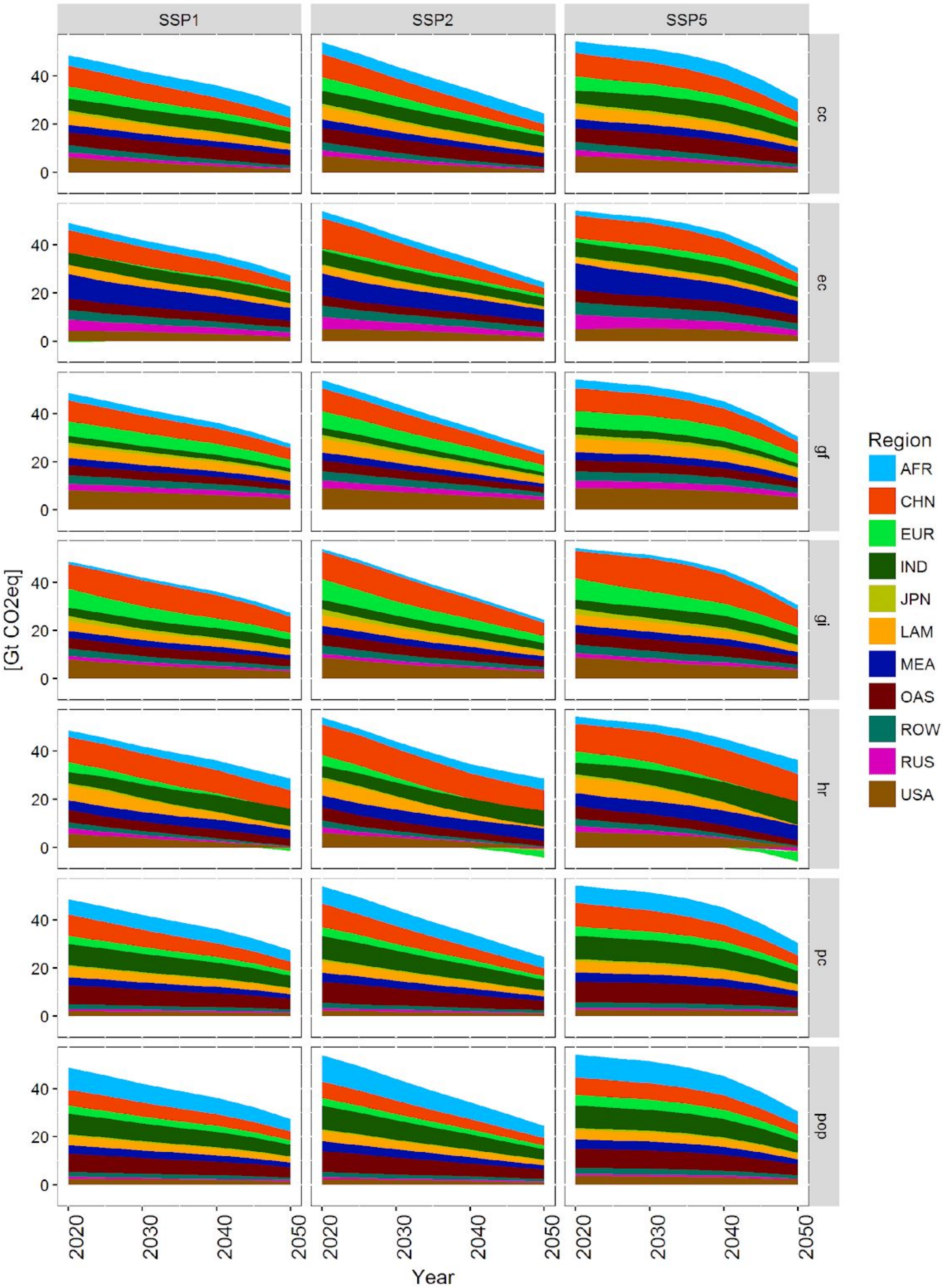


Fig. S.1: Distribution of emission allowances until 2050 under different burden sharing schemes and SSPs

Table S.1: Regional mitigation costs compared to global average (+ above average; o around average; - below average)

	AFR	CHN	EUR	IND	LAM	MEA	OAS	RUS	USA
CC	o	o	o/-	o/+	o/-	++	o	++	o/-
EC	o/+	o	o	o/+	o	o/+	o	o/+	o/-
GF	+	o/-	o/-	++	-	++	o/+	+	-
GI	++	-	-	+	o/-	++	o	++	-
HR	---	-	+	---	+	o/-	o	+++	o/+
PC	o/-	o	o/-	o	o/-	++	o/-	++	o/-
POP	-	o	o/-	o	o/-	++	o/-	++	o/-

Table S.2: Cumulated Permit trade value (discounted by 5% per year) in 2100 (in bill. US$2005); positive values indicate net costs, negative values net revenues

		AFR	CHN	EUR	IND	LAM	MEA	OAS	RUS	USA
CC	SSP1	-440	-45	140	-8	176	255	-420	238	58
	SSP2	-422	86	435	-287	203	360	-289	182	-76
	SSP5	16	-357	1279	782	471	-465	-259	85	-394
EC	SSP1	-97	359	1801	-177	568	-2261	47	-763	708
	SSP2	68	-13	2117	-665	1456	-2497	821	-1294	744
	SSP5	762	1148	2666	-716	2552	-4433	201	-2346	1483
GF	SSP1	698	-307	-582	1423	-48	370	459	-200	-1424
	SSP2	1265	-334	-645	1793	-88	535	974	-434	-2186
	SSP5	1793	-608	23	3413	65	-277	1340	-693	-3058
GI	SSP1	971	-1381	-585	602	258	369	142	235	-699
	SSP2	1854	-1608	-834	800	292	438	582	180	-1332
	SSP5	2869	-3312	60	2088	711	-233	862	83	-1796
HR	SSP1	-2489	-1568	2831	-3269	1233	-1045	-291	1298	2028
	SSP2	-5577	-3901	7689	-5963	2905	-3929	-587	2224	4803
	SSP5	-16186	-8310	17751	-15513	9636	-8998	1143	7492	8954
PC	SSP1	-723	-29	474	-481	241	228	-719	363	727
	SSP2	-910	131	930	-1057	305	311	-771	392	903
	SSP5	-615	-302	1855	-224	626	-525	-884	370	812
POP	SSP1	-1089	310	433	-383	300	216	-646	374	596
	SSP2	-1730	781	1004	-965	378	258	-693	409	831
	SSP5	-1367	1031	2243	287	1412	-828	-864	662	113

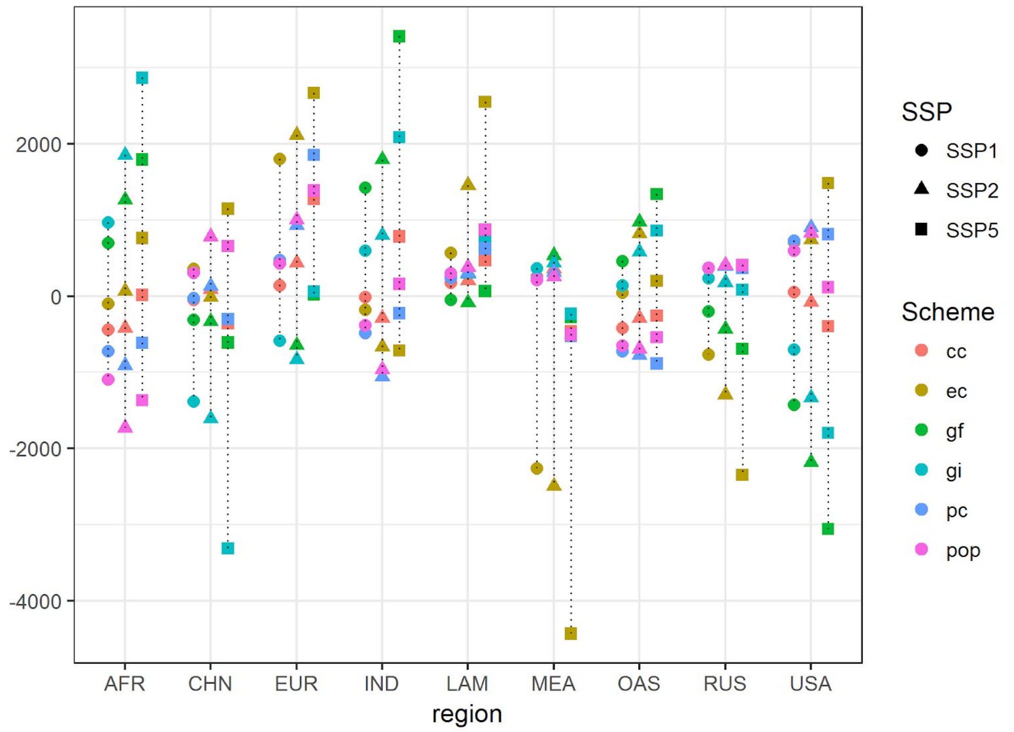


Fig. S.2: Cumulated Permit trade value (discounted by 5% per year) in 2100 (in bill. US$2005); positive values indicate net costs, negative values net revenues

Table S.3: Contribution of permit trade to overall mitigation costs (in percentage points)

		AFR	CHN	EUR	IND	LAM	MEA	OAS	RUS	USA
CC	SSP1	-0.8	0.0	0.0	0.0	0.2	0.4	-0.5	1.0	0.0
	SSP2	-0.9	0.1	0.2	-0.6	0.2	0.6	-0.4	0.8	0.0
	SSP5	0.0	-0.2	0.4	1.2	0.5	-0.6	-0.3	0.3	-0.1
EC	SSP1	-0.2	0.3	0.6	-0.3	0.6	-3.3	0.1	-3.2	0.3
	SSP2	0.2	0.0	0.7	-1.3	1.7	-3.9	1.1	-5.6	0.3
	SSP5	1.2	0.7	0.8	-1.1	2.6	-6.1	0.2	-8.5	0.4
GF	SSP1	1.4	-0.2	-0.2	2.4	0.0	0.5	0.5	-0.8	-0.5
	SSP2	2.8	-0.3	-0.2	3.5	-0.1	0.8	1.3	-1.9	-0.8
	SSP5	2.9	-0.4	0.0	5.1	0.1	-0.4	1.4	-2.5	-0.9
GI	SSP1	1.9	-1.0	-0.2	1.0	0.3	0.5	0.2	1.0	-0.3
	SSP2	4.1	-1.3	-0.3	1.6	0.3	0.7	0.8	0.8	-0.5
	SSP5	4.6	-2.1	0.0	3.1	0.7	-0.3	0.9	0.3	-0.5
HR	SSP1	-4.8	-1.1	0.9	-5.5	1.4	-1.5	-0.4	5.5	0.7
	SSP2	-12.4	-3.2	2.7	-11.6	3.4	-6.1	-0.8	9.7	1.8
	SSP5	-26.2	-5.3	5.1	-23.2	9.9	-12.3	1.2	27.3	2.6
PC	SSP1	-1.4	0.0	0.2	-0.8	0.3	0.3	-0.9	1.5	0.3
	SSP2	-2.0	0.1	0.3	-2.1	0.4	0.5	-1.0	1.7	0.3
	SSP5	-1.0	-0.2	0.5	-0.3	0.6	-0.7	-0.9	1.3	0.2
POP	SSP1	-2.1	0.2	0.1	-0.6	0.3	0.3	-0.8	1.6	0.2
	SSP2	-3.8	0.6	0.4	-1.9	0.4	0.4	-0.9	1.8	0.3
	SSP5	-2.2	0.4	0.4	0.2	0.9	-0.7	-0.6	1.5	0.0

A.6 POP-07 scenarios

Capital mobility in REMIND ensures that capital moves (i.e. is traded) between all regions until the rates of return of capital equalize. The Keynes-Ramsey rule applies, according to which the growth rate of per capita consumption in the balanced growth path is equal across all regions (assuming all regions have the same pure rate of time preference).

An upper bound on consumption losses, as in the POP-07 scenarios (section 6.1), may cause a distortion of the balanced growth path as demonstrated in Figure A.2. Whereas in the SSP5-POP scenario all trajectories of consumption losses are parallel to each other, this does not hold any longer for the consumption losses in the SSP5-POP-07 scenario.

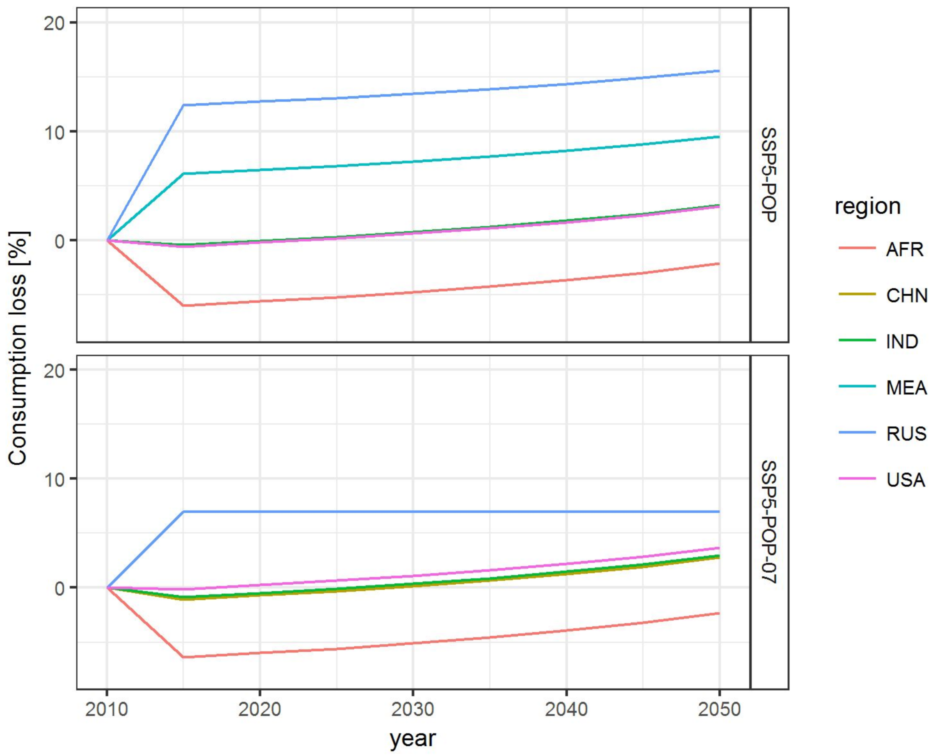


Fig. S.3: Consumption losses over time in SSP5-POP (upper panel) and SSP5-POP-07 scenario (lower panel)

The applied bound prevents in the case of MEA and Russia a further outflow of capital that would be needed in order to meet the intertemporal budget constraint. This directly follows from the interaction of consumption *C* and capital export *X* in the budget constraint and the contribution of capital (composite good) exports in the intertemporal trade balance. In the reduced form, the budget constraint reads as

$$C_t = Y_t + M_t^g - X_t^g - I$$

(with *Y* representing GDP, *M* import of composite good *g*, and *I* macroeconomic investments).

The intertemporal trade balance sums up net exports of the composite good and other goods *o* evaluated by respective net present value prices *p*:

$$B = \sum_t \left(p_t^g \left(X_t^g - M_t^g \right) + \sum_o p_t^o (X_t^o - M_t^o) \right)$$

With C* as the optimal consumption in the unconstrained model it holds:

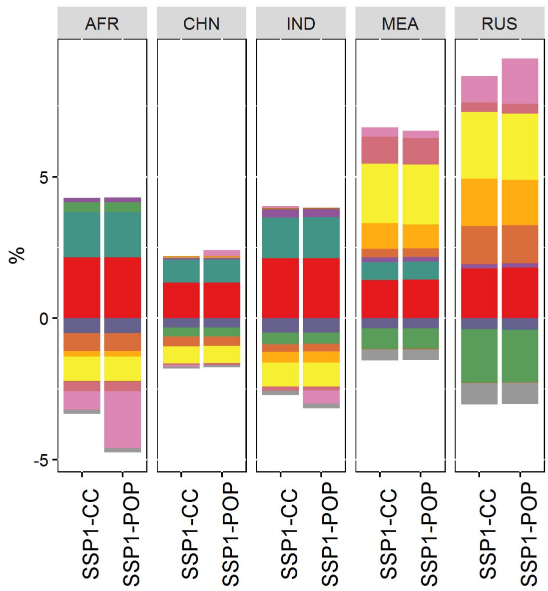
if $C_t > C_t^*$ then $B < 0$.

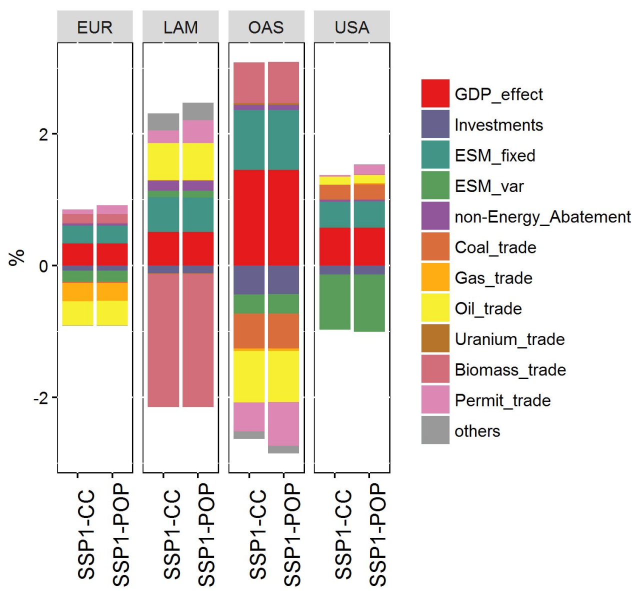
In the POP-07 scenarios, the model solution converges to a point where MEA and Russia accumulate a deficit (*B<0*) and all other regions a surplus in the intertemporal trade balance. We interpret this deficit as a financial transfer by the surplus regions that confines the consumption losses in the deficit regions according to the specified bound.

A.7 Decomposition analysis

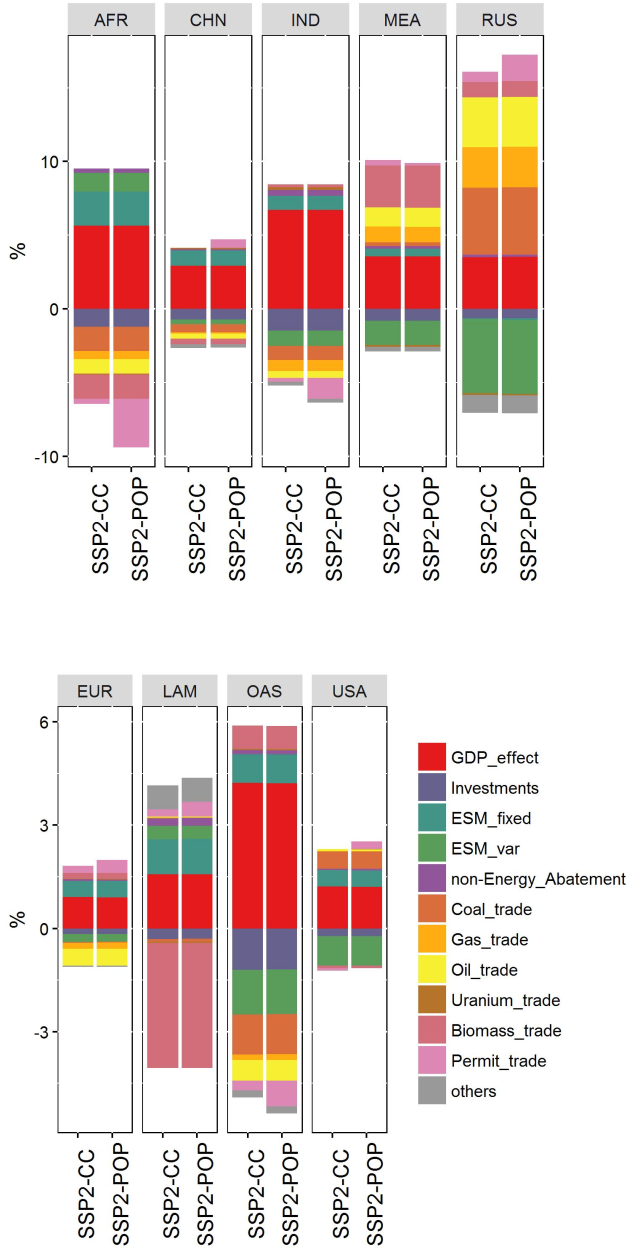
A decomposition technique as described in Aboumahboub et al. (2014) is applied. The decomposition of mitigation costs is discussed by illustrations of the CC and POP scenarios (see Fig. S.4). The decomposition for the TAX scenarios is equal to the two discussed scenarios for all components but the permit trade. The same applies to the burden sharing schemes analyzed in section 5. The permit trade value is zero in the TAX scenarios. This equivalence of the decomposition is due to a property of REMIND as general equilibrium model with intertemporal capital trade which allows the separation of equity and efficiency (cf. section 3.2).

a.

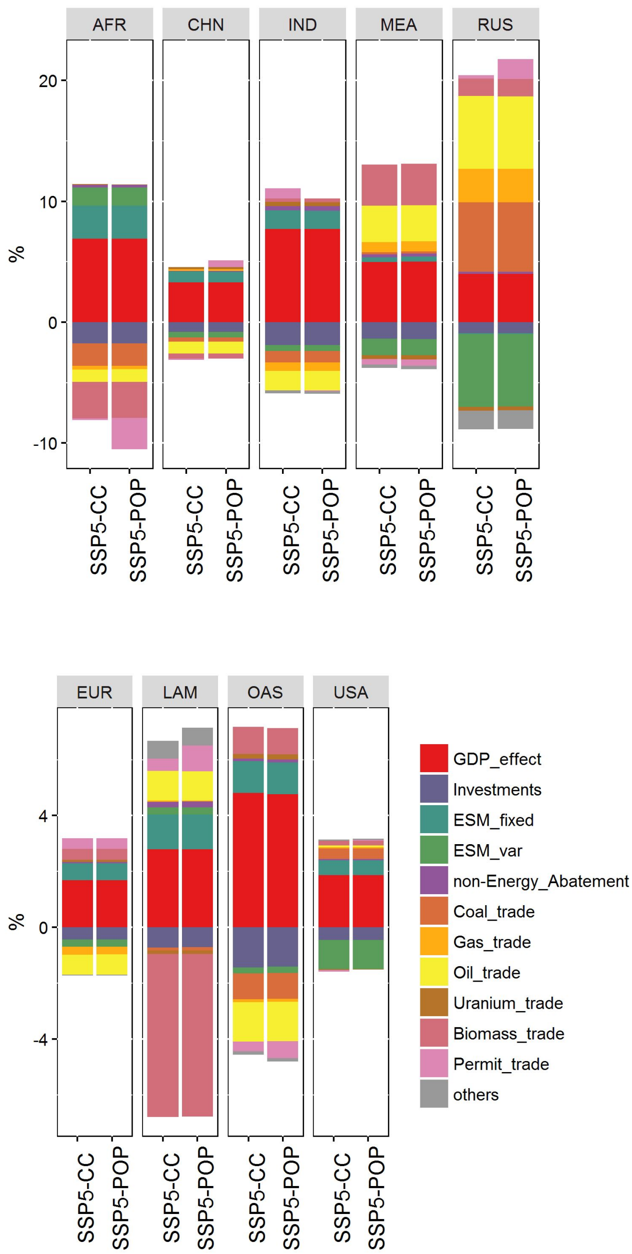




b.


AFR
CHN
IND
MEA
RUS
%
10
0
-10
SSP2-CC
SSP2-POP
EUR
LAM
OAS
USA
6
3
0
-3
GDP_effect
Investments
ESM_fixed
ESM_var
non-Energy_Abatement
Coal_trade
Gas_trade
Oil_trade
Uranium_trade
Biomass_trade
Permit_trade
others

c.



S. 4: Decomposition of mitigation costs (panel a: SSP1, panel b: SSP2, panel c: SSP5)

Qualitatively, the decomposition shows a similar pattern across all SSPs. Overall, direct GDP losses represent a major part in all regions. However, despite similar GDP growth in SSP1 and SSP2, mitigation costs due to GDP losses are smaller in SSP1 because of higher energy efficiency and a higher preference for renewable energy. Both components reduce the carbon dioxide emission per unit of GDP already in the baseline. Mitigation costs contributions from trade are also large. Negative consumption effects due to decreasing fossil resource prices can be seen in MEA and Russia (to a smaller extent also in USA), and positive effects in AFR, China, India, OAS and EUR. In Russia and MEA, trade effects account for around 50% of the mitigation costs in all scenarios. Figures are even higher in Russia when permit imports are additionally taken into account. In both regions biofuels substitute fossils, hence biomass imports increase in policy scenarios. Consequently, the negative trade effect overcompensates savings from lower extraction and fuel costs. The only significant difference between the different scenarios of the same SSP type concerns the permit trade effect. It will be discussed in the next section.

In how far do differences in the mitigation cost composition mirror differences in the socio-economic assumptions across regions and across SSPs?

AFR and India show the highest direct growth impact (GDP effect), which is due to the assumption of relatively high growth rates in all scenarios (Dellink et al., 2017). The slightly lower economic growth rates and the contained population growth in SSP1 (cf. KC and Lutz, 2017) result in a somewhat lower contribution of the GDP effect in SSP1. On the other hand, a higher share of mitigation costs, compared to SSP2 and SSP5, is due to energy system investment costs (ESM_fixed). This indicates first that additional investments in carbon-free technologies are requested independently of the economic growth rate. Secondly, risk aversion on external environmental effects associated with large-scale biomass technologies (e.g. loss of biodiversity, reduction of food security) results in SSP1 in a preference to other forms of carbon–free energy technologies, like solar and wind, which have a higher fixed cost share than biomass technologies. With respect to the trade effects, AFR and India profit from lower prices on the energy markets – in particular with oil imports in SSP1. With a higher energy demand in SSP2 and in particular SSP5 (Bauer et al. 2017, Kriegler at al. 2017, Fricko et al., 2017), biomass plays a more important role – mainly as a unique technology of generating negative emissions, which are needed to compensate for remaining fossil fuel emissions. A higher share of negative mitigation costs is generated in AFR in SSP2 and SSP5 by revenues from biomass exports (both due to higher export quantities and higher prices). The biomass trade effect is most pronounced for LAM. LAM is the major exporter of biomass and profits from a price increase. A higher global demand for biomass in SSP5 based on a higher preference for this energy carrier and the need to compensate for initial higher fossil fuel consumption, enable LAM to scale up related trade benefits. Consequently, LAM faces even lower mitigation costs in SSP5 than in SSP1.

In all other regions, we see the same variation across the SSPs with respect to the GDP effect (lower share in SSP1) and energy system investment costs (higher share in SSP1), like in AFR and India. While China, OAS, and EUR also demonstrate a similar pattern regarding the energy trade effect (higher negative shares in SSP1), the opposite (higher positive shares in SSP1) applies to MEA and the USA. In particular, the major oil exporter MEA faces a higher share of mitigation costs due to losses in oil trade in SSP1. In Russia, the gas trade has an equal share of the mitigation costs in SSP1 as the oil trade, whereas the coal trade effect takes a much higher share in SSP2 and SSP5. This is a direct consequence of the high level of coal consumption globally in the baselines of SSP2 and SSP5 and related to the abundance of cheap coal in both scenario worlds. Compared to other regions, the USA exhibits a high negative share (i.e. gains) from lower fuel expenditures in SSP1. Overall, the decomposition analysis uncovers significant differences as well as qualitative similarities in the mitigation cost structure across the SSP scenarios.

A.8 Permit trading

Permit trading and in particular the allocation of permits are key components of burden sharing. Based on an agreed allocation of emission permits, transfers on the carbon market represent a well-defined form of climate finance. However, any type of climate finance implying the same transfers will yield the same burden sharing result.

Fig. S.5 presents the trade pattern in scenarios with a large amount of permit trade – SSP2-POP and SSP5-POP, peaking at 4.2 and 3.7 Gt CO_2eq in 2025, respectively. The SSP1-POP scenario peaks at a lower level of around 3.3 Gt CO_2eq in 2025. The trade pattern is the same in all POP scenarios: highest trade level in the beginning, a decreasing trade level until 2060 and a slight increase and stabilization at moderate levels towards the end of the century. The permit trade is much lower in the first half of the century in the CC scenarios (it hardly exceeds 1.5 Gt CO_2eq in SSP5-CC and even less in SSP2-CC and SSP1-CC), but the trade structure (i.e. the distribution of exporters and importers) is similar. This includes the switch of exporters and importers in 2060, which in particular holds for the big players on the carbon market: AFR, India, OAS, USA and China.

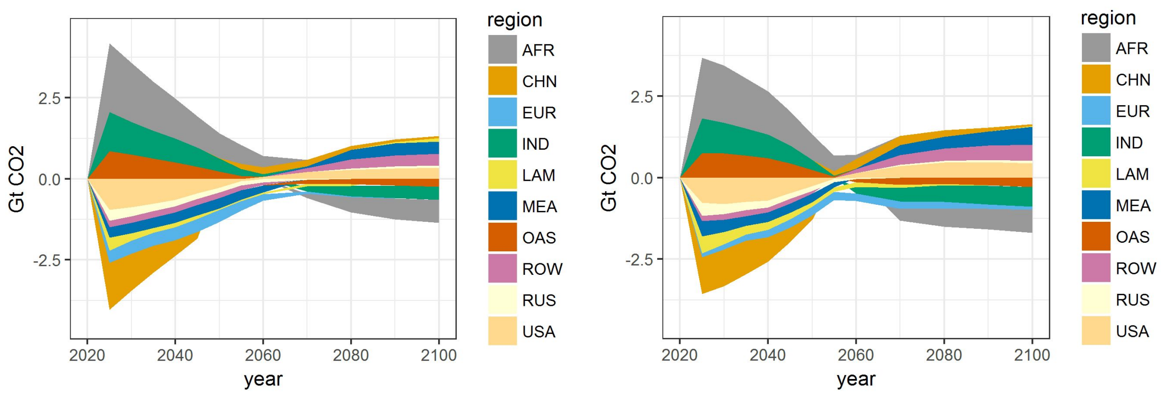


Fig. S.5: Permit trade (in Gt CO_2eq); left panel: SSP2-POP; right panel: SSP5-POP

The switch of exporters and importers does not at all mean that the contribution of the permit trade to the mitigation costs is well-balanced. The contribution of the permit trade depends on the carbon price as well as on the discount factor. The effects of both nearly cancel out each other. Thus, the areas in Fig. S.5 roughly illustrate for which regions we may expect positive or negative contributions to mitigation costs.

While details on these contributions are provided in Table S.3, another important information should be highlighted – the magnitude of revenues and transfers. Details on the cumulative amount of transfers are shown in Table S.2 and Fig. S.2. Furthermore, as Table S.4 demonstrates, transfers can be huge measured as share of GDP. Figures are high in the short term due to the large amount of permits traded and in the long term as a result of high carbon prices. Due to the initial existence of a fragmented climate policy regime, we see highest relative transfer levels with the beginning of the emissions trading system in 2025 and 2030. In SSP5-POP and SSP2-POP, we see maximum values of around 20% of GDP for AFR; for India the initial revenues are between 4% and 5% of GDP. These revenues on the carbon market are accompanied by payments that amount in 2030 to around 4% of

GDP for Russia, around 2% of GDP for China and MEA, and around 1% of GDP for LAM and USA (see Table S.4). Later in the century, substantial transfers flow in the opposite direction.

Permit trading in the equality-based scenarios analyzed (CC and POP) implies huge financial transfers, which however is put into perspective when compared to alternative burden sharing schemes as investigated in section 5. Improved institutions are required for administering financial transfers with care to avoid adverse effects, such as a “climate finance curse” (Jakob et al., 2015, Kornek et al., 2017).

Table S.4: Share of Permit trade value on GDP in 2030, 2050 and 2100 (in %)

		AFR	CHN	EUR	IND	LAM	MEA	OAS	RUS	USA
SSP1-POP	2030	8.6	-0.6	-0.1	1.9	-0.4	-0.6	1.1	-1.8	-0.4
	2050	3.1	-0.2	-0.3	0.8	-0.3	-0.7	0.9	-2.0	-0.4
	2100	-2.0	0.2	0.3	-3.9	0.0	2.9	-1.4	1.2	2.1
SSP1-CC	2030	3.1	-0.3	0.0	0.5	-0.1	-0.8	0.6	-0.5	-0.1
	2050	2.5	-0.1	-0.3	1.0	-0.3	-0.8	0.9	-2.0	-0.4
	2100	-2.3	2.4	0.2	-3.8	0.1	2.9	-1.3	1.4	2.0
SSP2-POP	2030	18.8	-1.4	-0.4	4.6	-0.7	-1.3	2.1	-3.0	-0.8
	2050	7.1	0.0	-0.7	2.2	-0.2	-2.0	0.9	-3.0	-0.5
	2100	-7.4	1.3	0.0	-7.3	2.1	8.8	-3.4	8.2	4.3
SSP2-CC	2030	6.3	-0.7	0.0	1.6	-0.2	-1.8	1.1	-0.5	-0.2
	2050	5.4	0.3	-0.7	2.5	-0.2	-0.2	1.0	-3.0	-0.6
	2100	-8.0	2.1	0.0	-7.2	2.3	8.7	-3.4	8.3	4.2
SSP5-POP	2030	17.6	-1.3	-0.2	4.3	-1.2	-1.6	2.1	-3.2	-0.8
	2050	5.7	-0.3	-0.5	1.5	-0.7	-1.7	0.9	-2.8	-0.5
	2100	-7.0	1.3	-0.7	-11.1	0.4	15.4	-4.1	9.6	3.3
SSP5-CC	2030	7.2	-0.6	0.0	1.6	-0.3	-1.9	1.3	-0.5	-0.4
	2050	4.8	0.0	-0.7	2.0	-0.5	-1.5	1.1	-2.7	-0.8
	2100	-8.0	3.6	-1.0	-10.3	1.1	15.4	-3.5	10.3	2.8

References

Aboumahboub, T., G. Luderer, E. Kriegler, M. Leimbach, N. Bauer, M. Pehl, L. Baumstark (2014). "On the Regional Distribution of Climate Mitigation Costs: The Impact of Delayed Cooperative Action." Climate Change Economics 5: 1440002. doi:10.1142/S2010007814400028.

Bauer, N., K. Calvin, J. Emmerling, O. Fricko, S. Fujimori, J. Hilaire, J. Eomb, V. Krey, E. Kriegler, I. Mouratiadou (2017). "Shared Socio-Economic Pathways of the Energy Sector – Quantifying the Narratives." Global Environmental Change 42: 316-330.

Bauer, N., L. Baumstark, M. Leimbach (2012). „The REMIND-R model: the role of renewables in the low-carbon transformation - first-best vs. second best worlds." Climatic Change 114: 145-168.

Bertram, C., G. Luderer, R. C. Pietzcker, E. Schmid, E. Kriegler, O. Edenhofer (2015). "Complementing Carbon Prices with Technology Policies to Keep Climate Targets within Reach." Nature Climate Change 5: 235-239.

Dellink, R., J. Chateau, E. Lanzi, B. Magne (2017). „Long-term growth projections in Shared Socioeconomic Pathways." Global Environmental Change 42: 200-214.

Fricko, O., P. Havlik, J. Roegelj, Z. Klimont, M. Gusti, N. Johnson, P. Kolp, M. Strubegger, H. Valin et al. (2017). "The marker quantification of the Shared Socioeconomic Pathway 2: A middle-of-the-road scenario for the 21st century." Global Environmental Change 42: 251-267.

Jakob, M., Steckel, J. C., Flachsland, C., Baumstark, L. (2015). „Climate finance for developing country mitigation: blessing or curse?" Climate and Development 7: 1-15.

KC, S., W. Lutz (2017). „The Human Core of the SSPs: Population Scenarios by Age , Sex and Level of Education for all Countries to 2100." Global Environmental Change 42: 181-192.

Klein, D., F. Humpenöder, N. Bauer, J.P. Dietrich, A. Popp, B. Bodirsky, M. Bonsch, H. Lotze-Campen, H. (2014). "The global economic long-term potential of modern biomass in a climate-constrained world", Environmental Research Letters, Vol. 9, 074017.

Kriegler, E., N. Bauer, A. Popp, F. Humpenöder, M. Leimbach, J. Strefler, L. Baumstark, et al (2017). "Fossil-Fueled Development (SSP5): An Energy and Resource Intensive Scenario for the 21st Century." Global Environmental Change 42: 297–315.

Leimbach M., N. Bauer, L. Baumstark, M. Lüken, O. Edenhofer (2010). „Technological Change and International Trade – Insights from REMIND-R." Energy Journal 31: 109-136.

Lotze-Campen, H., C. Müller, A. Bondeau, S. Rost, A. Popp, W. Lucht (2008). "Global food demand, productivity growth, and the scarcity of land and water resources: a spatially explicit mathematical programming approach." Agricultural Economics 39: 325–338.

Luderer, G., M. Leimbach, N. Bauer, E. Kriegler, L. Baumstark, C. Bertram, A. Giannousakis, et al. (2015). "Description of the REMIND Model (Version 1.6)." SSRN Scholarly Paper. Rochester, NY: Social Science Research Network, November 30, 2015. https://papers.ssrn.com/abstract=2697070.

Meinshausen, M., S. C. B. Raper, T. M. L. Wigley (2011). “Emulating Coupled Atmosphere-Ocean and Carbon Cycle Models with a Simpler Model, MAGICC6–Part 1: Model Description and Calibration.” Atmos. Chem. Phys 11: 1417–1456.

References

Arrow, K. et al. (July 26, 2013). “Determining Benefits and Costs for Future Generations”. In: *Science* 341.6144, pp. 349–350. ISSN: 0036-8075, 1095-9203. DOI: 10.1126/science.1235665.

Baker, Erin (Feb. 1, 2006). “Increasing Risk and Increasing Informativeness: Equivalence Theorems”. In: *Operations Research* 54.1, pp. 26–36. ISSN: 0030-364X. DOI: 10.1287/opre.1050.0213.

Baker, Erin et al. (May 1, 2015). “Future costs of key low-carbon energy technologies: Harmonization and aggregation of energy technology expert elicitation data”. In: *Energy Policy* 80, pp. 219–232. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2014.10.008.

Bauer, Nico et al. (July 2, 2018). “Global energy sector emission reductions and bioenergy use: overview of the bioenergy demand phase of the EMF-33 model comparison”. In: *Climatic Change*. ISSN: 1573-1480. DOI: 10.1007/s10584-018-2226-y.

Bauer, Nico et al. (Dec. 2020). “Quantification of an efficiency–sovereignty trade-off in climate policy”. In: *Nature* 588.7837. Number: 7837 Publisher: Nature Publishing Group, pp. 261–266. ISSN: 1476-4687. DOI: 10.1038/s41586-020-2982-5.

Bertram, Christoph et al. (Feb. 2, 2015). “Complementing carbon prices with technology policies to keep climate targets within reach”. In: *Nature Climate Change* advance online publication. ISSN: 1758-678X. DOI: 10.1038/nclimate2514.

Bertram, Christoph et al. (2018). “Targeted policies can compensate most of the increased sustainability risks in 1.5 °C mitigation scenarios”. In: *Environmental Research Letters* 13.6, p. 064038. ISSN: 1748-9326. DOI: 10.1088/1748-9326/aac3ec.

Bosetti, Valentina et al. (May 1, 2015). “Sensitivity to energy technology costs: A multi-model comparison analysis”. In: *Energy Policy* 80, pp. 244–263. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2014.12.012.

Broeren, M. L. M., D. Saygin, and M. K. Patel (Jan. 1, 2014). “Forecasting global developments in the basic chemical industry for environmental policy analysis”. In:

Energy Policy 64, pp. 273–287. ISSN: 0301-4215. DOI: 10.1016/j.enpol.2013.09.025.

Burke, M. et al. (Apr. 15, 2016). "Opportunities for advances in climate change economics". In: *Science* 352.6283, pp. 292–293. ISSN: 0036-8075, 1095-9203. DOI: 10.1126/science.aad9634.

Creutzig, Felix et al. (Apr. 2018). "Towards demand-side solutions for mitigating climate change". In: *Nature Climate Change* 8.4, pp. 260–263. ISSN: 1758-6798. DOI: 10.1038/s41558-018-0121-1.

Golub, Alexander, Daiju Narita, and Matthias G. W. Schmidt (Apr. 1, 2014). "Uncertainty in Integrated Assessment Models of Climate Change: Alternative Analytical Approaches". In: *Environmental Modeling & Assessment* 19.2, pp. 99–109. ISSN: 1420-2026, 1573-2967. DOI: 10.1007/s10666-013-9386-y.

Hall, Jim W. et al. (Oct. 1, 2012). "Robust Climate Policies Under Uncertainty: A Comparison of Robust Decision Making and Info-Gap Methods". In: *Risk Analysis* 32.10, pp. 1657–1672. ISSN: 1539-6924. DOI: 10.1111/j.1539-6924.2012.01802.x.

Held, Hermann (Jan. 1, 2019). "Cost Risk Analysis: Dynamically Consistent Decision-Making under Climate Targets". In: *Environmental and Resource Economics* 72.1, pp. 247–261. ISSN: 1573-1502. DOI: 10.1007/s10640-018-0288-y.

Hotelling, Harold (Apr. 1, 1931). "The Economics of Exhaustible Resources". In: *Journal of Political Economy* 39.2. Publisher: The University of Chicago Press, pp. 137–175. ISSN: 0022-3808. DOI: 10.1086/254195.

Kann, Antje and John P. Weyant (Jan. 1, 2000). "Approaches for performing uncertainty analysis in large-scale energy/economic policy models". In: *Environmental Modeling & Assessment* 5.1, pp. 29–46. ISSN: 1420-2026, 1573-2967. DOI: 10.1023/A:1019041023520.

King, Andrew D. and Luke J. Harrington (2018). "The Inequality of Climate Change From 1.5 to 2°C of Global Warming". In: *Geophysical Research Letters* 45.10. _eprint: https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2018GL078430, pp. 5030–5033. ISSN: 1944-8007. DOI: https://doi.org/10.1029/2018GL078430.

Kriegler, Elmar et al. (Feb. 1, 2014a). "A new scenario framework for climate change research: the concept of shared climate policy assumptions". In: *Climatic Change* 122.3, pp. 401–414. ISSN: 0165-0009, 1573-1480. DOI: 10.1007/s10584-013-0971-5.

Kriegler, Elmar et al. (Jan. 28, 2014b). "The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies". In: *Climatic Change* 123.3. 00138, pp. 353–367. ISSN: 0165-0009, 1573-1480. DOI: 10.1007/s10584-013-0953-7.

Lara, M. De and L. Gilotte (2009). "Precautionary Effect and Variations of the Value of Information". In: *Uncertainty and Environmental Decision Making*. Ed. by Jerzy A.

Filar and Alain Haurie. International Series in Operations Research & Management Science 138. Springer US, pp. 239–253. ISBN: 978-1-4419-1128-5 978-1-4419-1129-2. DOI: 10.1007/978-1-4419-1129-2_8.

Lempert, Robert J. et al. (Apr. 1, 2006). "A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios". In: *Management Science* 52.4, pp. 514–528. ISSN: 0025-1909. DOI: 10.1287/mnsc.1050.0472.

Levesque, Antoine et al. (Apr. 1, 2018). "How much energy will buildings consume in 2100? A global perspective within a scenario framework". In: *Energy* 148. tex.ids: levesque_how_2018-1, pp. 514–527. ISSN: 0360-5442. DOI: 10.1016/j.energy.2018.01.139.

Lorenz, Alexander et al. (Feb. 1, 2012). "How to measure the importance of climate risk for determining optimal global abatement policies?" In: *Climate Change Economics* 03.1, p. 1250004. ISSN: 2010-0078. DOI: 10.1142/S2010007812500042.

Luderer, Gunnar et al. (Nov. 30, 2015). *Description of the REMIND Model (Version 1.6)*. SSRN Scholarly Paper ID 2697070. Rochester, NY: Social Science Research Network.

Luderer, Gunnar et al. (July 2018). "Residual fossil CO 2 emissions in 1.5–2 °C pathways". In: *Nature Climate Change* 8.7, p. 626. ISSN: 1758-6798. DOI: 10.1038/s41558-018-0198-6.

Luderer, Gunnar et al. (2021). "When the most valuable becomes the cheapest: Electrification of global energy towards climate neutral energy systems". In: *forthcoming*.

Marangoni, G. et al. (Jan. 16, 2017). "Sensitivity of projected long-term CO2 emissions across the Shared Socioeconomic Pathways". In: *Nature Climate Change* advance online publication. 00000. ISSN: 1758-678X. DOI: 10.1038/nclimate3199.

Moss, Richard H. et al. (Feb. 11, 2010). "The next generation of scenarios for climate change research and assessment". In: *Nature* 463.7282, pp. 747–756. ISSN: 0028-0836. DOI: 10.1038/nature08823.

O'Neill, Brian C. et al. (Feb. 1, 2014). "A new scenario framework for climate change research: the concept of shared socioeconomic pathways". In: *Climatic Change* 122.3, pp. 387–400. ISSN: 0165-0009, 1573-1480. DOI: 10.1007/s10584-013-0905-2.

Pietzcker, Robert C. et al. (Jan. 1, 2014). "Long-term transport energy demand and climate policy: Alternative visions on transport decarbonization in energy-economy models". In: *Energy* 64, pp. 95–108. ISSN: 0360-5442. DOI: 10.1016/j.energy.2013.08.059.

Popp, Alexander et al. (July 2011). "The economic potential of bioenergy for climate change mitigation with special attention given to implications for the land system".

In: *Environmental Research Letters* 6.3. Publisher: IOP Publishing, p. 034017. ISSN: 1748-9326. DOI: 10.1088/1748-9326/6/3/034017.

Riahi, Keywan et al. (Jan. 2017). "The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview". In: *Global Environmental Change* 42, pp. 153–168. ISSN: 0959-3780. DOI: 10.1016/j.gloenvcha.2016.05.009.

Rogelj, Joeri et al. (Sept. 2019). "A new scenario logic for the Paris Agreement long-term temperature goal". In: *Nature* 573.7774, pp. 357–363. ISSN: 1476-4687. DOI: 10.1038/s41586-019-1541-4.

Schultes, Anselm et al. (Aug. 15, 2020). *Economic damages from on-going climate change imply deeper near-term emission cuts.*

Strefler, Jessica et al. (2020). "Alternative carbon price trajectories can avoid excessive carbon removal". In: *Nature Communications (accepted).*

Tavoni, Massimo et al. (Nov. 1, 2013). "The distribution of the major economies' effort in the durban platform scenarios". In: *Climate Change Economics* 04.4, p. 1340009. ISSN: 2010-0078. DOI: 10.1142/S2010007813400095.

Traeger, Christian P. (2009). "Recent Developments in the Intertemporal Modeling of Uncertainty". In: *Annual Review of Resource Economics* 1.1, pp. 261–286. DOI: 10.1146/annurev.resource.050708.144242.

UNFCCC (2015). "Paris Agreement". In: *https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement.*

Vogt-Schilb, Adrien, Guy Meunier, and Stéphane Hallegatte (Mar. 1, 2018). "When starting with the most expensive option makes sense: Optimal timing, cost and sectoral allocation of abatement investment". In: *Journal of Environmental Economics and Management* 88, pp. 210–233. ISSN: 0095-0696. DOI: 10.1016/j.jeem.2017.12.001.

Weitzman, Martin L (Jan. 28, 2009). "On Modeling and Interpreting the Economics of Catastrophic Climate Change". In: *The Review of Economics and Statistics* 91.1. Publisher: MIT Press, pp. 1–19. ISSN: 0034-6535. DOI: 10.1162/rest.91.1.1.

Wenz, Leonie et al. (July 2020). "Road to glory or highway to hell? Global road access and climate change mitigation". In: *Environmental Research Letters* 15.7. Publisher: IOP Publishing, p. 075010. ISSN: 1748-9326. DOI: 10.1088/1748-9326/ab858d.