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Climate cost modelling – analysis of damage and mitigation frameworks and guidance for political use

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Climate cost modelling – analysis of damage and mitigation frameworks and guidance for political use

by

Dr. Quirin Oberpriller, Martin Peter, Dr. Jürg Füssler (Infras, Zürich) – project lead and lead Parts 1, 2 and 4 as well as Section 17.6.2 and Appendix A and B

Dr. Anne Zimmer, Dr. Tina Aboumahboub, Jessie Schleypen, Dr. Matthew Gidden, Dr. Michiel Schaeffer, Dr. Carl-Friedrich Schleussner (Climate Analytics, Berlin) – lead Part 3 as well as Appendix C and D

Prof. Dr. Reimund Schwarze, Kleinmachnow – Pre-screening and review Parts 2 und 4; lead Section 11

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Umweltbundesamt
Wörlitzer Platz 1
06844 Dessau-Roßlau
Tel: +49 340-2103-0
Fax: +49 340-2103-2285
buergerservice@uba.de
Internet: www.umweltbundesamt.de

/umweltbundesamt.de
/umweltbundesamt

Report performed by:
Infras
Binzstrasse 23
8045 Zurich
Switzerland

Climate Analytics
Ritterstraße 3
10969 Berlin
Germany

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Scientific supervision:
Section Economic and Social Environmental Issues, Sustainable Consumption
Astrid Matthey and Björn Bünger

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Abstract: Climate cost modelling – analysis of damage and mitigation frameworks and guidance for political use

This report provides a comprehensive overview of climate cost modelling, from the perspective of damage costs and mitigation costs respectively. It also provides guidance for policymakers on which framework shall be used to derive climate costs for different policy objectives. For both frameworks, the study describes the landscape of available models and their methods. It analyses the role and impact of different influencing factors and separates them into categories, such as scenarios, normative choices or structural elements. The report identifies and discusses the main sources of uncertainties and the range of the literature's values. It discusses limitations of interpreting model results — making assumptions and approaches of different climate models transparent. Finally, there is a practical guidance in four steps on the process to derive a climate cost 'price tag' targeted to a specific policy question. The internalisation of external costs calls for applying a damage costs framework, while identifying the necessary effort for complying with an agreed temperature limit requires mitigation costs, for example.

Kurzbeschreibung: Klimakostenmodellierung - Analyse der Ansätze Schadenskosten und Vermeidungskosten sowie Anleitung zur politischen Nutzung

Dieser Bericht gibt einen umfassenden Überblick über die Klimakostenmodellierung, jeweils aus der Perspektive der Schadenskosten und der Vermeidungskosten. Er bietet auch eine Anleitung für politische Entscheidungsträger, welcher Ansatz je nach politischem Ziele verwendet werden sollte, um Klimakosten abzuleiten. Für beide Ansätze beschreibt der Bericht die Landschaft der verfügbaren Modelle und deren Methoden. Er analysiert die Rolle und die Auswirkung verschiedener Einflussfaktoren und unterteilt sie in Kategorien, wie z.B. Szenarien, normative Entscheidungen oder strukturelle Elemente. Der Bericht identifiziert und diskutiert die Hauptquellen von Unsicherheiten und die Spannweite der Werte in der Literatur. Er diskutiert die Grenzen der Interpretation von Modellergebnissen und macht dabei Annahmen und Ansätze verschiedener Klimamodelle transparent. Schließlich bietet der Bericht eine praktische Anleitung in vier Schritten, um ein "Preisschild" für die Klimakosten zu bestimmen. Wichtig ist dabei, die spezifische politische Fragestellung zu berücksichtigen. So erfordert die Internalisierung externer Kosten die Anwendung von Schadenskosten, während der notwendige Aufwand für die Einhaltung eines vereinbarten Temperaturlimits Vermeidungskosten bedingt.

Table of content

List of figures

List of tables

List of abbreviations

AR5	5th Assessment Report of the Intergovernmental Panel on Climate Change
BAU	Business as Usual
BECCS	Bioenergy with CCS
BHM	Burke et al 2015
CCS	Carbon Capture and Storage / Sequestration
CDR	Carbon Dioxide Removal
DAC	Direct Air Capture
DACCS	Direct Air Capture with Carbon Storage
CB-IAM	Cost-Benefit Integrated Assessment Model
CE-IAM	Cost Effectiveness IAM
CGE	Computable General Equilibrium
CO2	Carbon Dioxide
DICE	Dynamic Integrated model of Climate and the Economy
DJO	Dell et al 2012
EC	European Commission
FUND	Framework for Uncertainty, Negotiation and Distribution Infrastructure Plan
GAP	Gross Agricultural Product
GHG	Greenhouse Gas(es)
GWP	Global Warming Potential
IAWG	Interagency Working Group
IPCC	International Panel on Climate Change
MAC	Marginal Abatement Cost Curve
NET	Negative Emission Technologies
NDC	Nationally Determined Contributions (in Paris-Agreement)
N_2O	Nitrous Oxide (Laughing Gas)
MAC	Marginal Abatement Costs
PAGE	Policy Analysis of the Greenhouse Effect
PDF	Probability Distribution Function
PPP	Purchasing Power Parity
PRTP	Pure Rate of Time Preference
RICE	Regional Integrated Climate-Economy
SCC	Social Cost of Carbon
SDR	Social Discount Rate
SLR	Sea Level Rise
SPA	Shared Policy Assumption
SRES	Special Report on Emission Scenarios

SSP	Socio-economic Pathways
SWF	Social Welfare Function
RCP	Representative Concentration Pathway
UNFCCC	United Nations Framework Convention on Climate Change
VRE	Variable Renewable Energy

Summary

Background and aims of the study

Climate change is one of the greatest challenges mankind currently faces. It will lead to significant damages even if constrained to a global mean temperature increase of 1.5°C above pre-industrial levels. Without such stringent mitigation efforts, damages will be even higher. Assessing the scale of the damages is important to strengthen political as well as public support for ambitious climate action. The current Method Convention 3.0 of the German Environment Agency thus recommends for greenhouse gas emissions in the year 2016 a cost rate of 180 $€_{2016}/tCO_{2eq}$ and a sensitivity analysis of 640 $€_{2016}/tCO_{2eq}$.These number are based on the model FUND, which calculates and aggregates damages for current and future generations. These results are strongly dependent on assumptions with respect to various influencing factors. For example, the discrepancy of UBA's numbers solely arise for assuming a pure rate of time preference (which is a crucial part of the discount rate) of 1% or 0%, respectively. For this and other influencing factors, there is an ongoing debate on a scientific, economic, social, and political level about the appropriate choice. Consequently, the estimates of climate damages in the scientific literature differ considerably.

Focusing on damages, the German Environment Agency uses the damage costs framework to derive "climate costs". Mitigation costs are the other framework to calculate climate costs in case the focus is on the costs to reduce greenhouse gas emissions. The commitment to the Paris Agreement, provides an important benchmark for the mitigation target, as countries in article 2 agreed to limit global mean temperature increase to "well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C". Mitigation costs estimations, however, are also subject to considerable uncertainty, as assumptions on influencing factors differ widely. Some challenges are the same as for damage costs (e.g. the discount rate), others are specific for mitigation costs (e.g. constraints on certain technology options).

As the following table shows, the choice of the appropriate framework depends on the policy objective.

Table A: Policy objectives and the appropriate frameworks

#	Policy Objective	Comments	Political Relevance
Damage costs are the appropriate framework			
D1	**Raise awareness of climate damages if policy is not acting**	**Related to "costs of inaction"**	**High**
D2	**Internalise external costs according to polluter-pays-principle**	**By means of a tax/levy or other market-based instruments; strong connection to definition of SCC**	**High**
D3	Monetize (avoided) climate damages related to a specific measure or policy instrument	Input to cost-benefit analysis, policy appraisal or regulatory impact assessment	Medium
D4	Determine benefits of a specific adaptation measure	Sector-specific, local damages required	Low
Mitigation costs are the appropriate framework			

M1	**Identify required policy effort (e.g. carbon tax / levy) to remain within a predefined temperature limit**	**The Paris Agreement defines internationally agreed temperature limit**	**High**
M2	Provide a benchmark for socially valuable mitigation measures (private and public) and policy instruments	Corresponds to the French approach ("Social Value of Mitigation Action")	Medium
M3	Assess the (total) costs of reaching a pre-defined mitigation target	To calculate total costs the marginal mitigation costs curve (MAC-curve) or the average mitigation costs are needed	Medium
M4	Assess mitigation costs related to a specific measure or policy instruments	Input to cost-benefit analysis, policy appraisal, or regulatory impact assessment	Medium
Both frameworks may be used			
B1	Provide information for internal shadow pricing of companies	Companies may use both frameworks	Medium
B2	Provide a benchmark value for the price of carbon credits in results-based finance schemes (e.g. Art 6.4 of Paris Agreement)	Price is usually determined by supply and demand; yet, contracting authority may provide benchmark or fix price	Low

Source: own illustration, Infras and Climate Analytics

Against this background, this study has the following objectives:

- Provide a comprehensive overview of the literature on the two frameworks to derive climate cost estimates (damages cost and mitigation cost).
- Analyse the significance and impact of different influencing factors and assumptions and create a typology
- Identify relevant policy objectives to provide information on climate costs and map objectives to the appropriate framework
- Recommend a procedure to quantify the climate costs for future Method Conventions of the German Environment Agency.

Conceptual frameworks to derive climate costs

Damages costs and mitigation costs are two frameworks to derive climate costs. The following table explains the basic conceptual differences and the areas of applicability.

Table B: Frameworks to derive climate costs

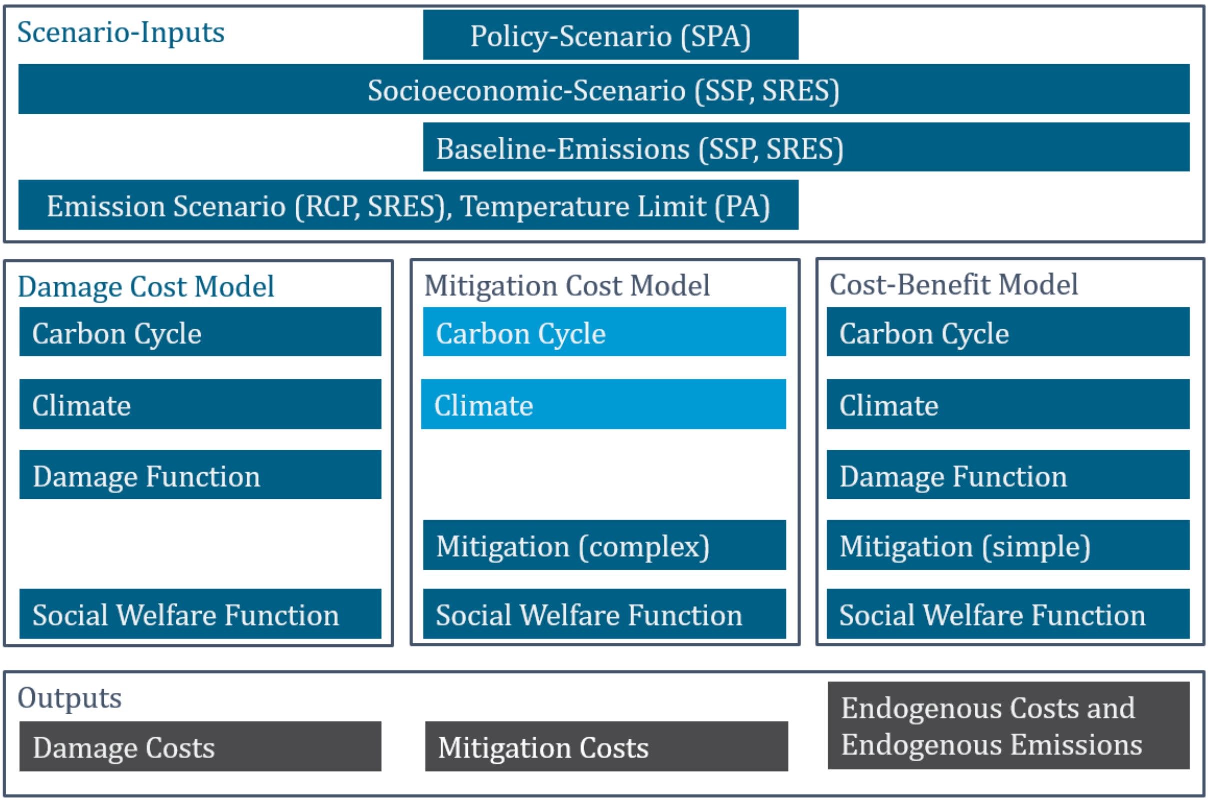
	Damage Costs	Mitigation Costs
Explanation	• Relate to the various damages caused by the emissions of greenhouses gases • Includes adaptation costs	• Accrue due to the implementation of measures to reduce emissions • May include co-benefits (e.g. clean air)

	• Often expressed in terms of social costs of carbon (SCC) • SCC are defined marginally, but damage costs may also be calculated as total or average costs • SCC usually increase if underlying emission pathway is higher • Covered in Part 2 of this report	• Several calculation approaches: economy-wide marginal, average or total costs compared to a baseline scenario • Refers to specific measures, specific sectors, or the whole economy • Increase with more ambitious mitigation efforts • Covered in Part 3 of this report
Applicability (Examples)	• Internalisation of external costs ("polluter pays"-principle) • Benefits in terms of avoided damages when conducting a cost-benefit analysis of a policy or specific mitigation measure	• Appropriate tax rate to achieve a predefined mitigation target (overall or for a specific sector) • Costs of a certain mitigation policy

Source: own illustration, Infras

The following Figure illustrates the inputs and outputs of the models, that use these frameworks. Model inputs are various types of scenarios. The models consist of various modules and the outputs are the resulting cost estimation (in grey).

Figure A: Inputs and modules of different types of climate cost models



Source: own illustration, Infras

The figure shows that there is a third modelling framework. Cost-benefit models consider damage and mitigation costs in parallel and are thus able to determine emissions endogenously (i.e. they determine an — according to the model — "optimal" emission path). This framework is, however, not in the focus of this study as it is conceptually problematic. Moreover, the Paris Agreement represents an international political consensus, and the corresponding emission path is thus a logical benchmark. There is little added-value to determine another emission path using cost-benefit models, whose results depend very much on the model assumptions.

It may still be useful to consider damage and mitigation costs in parallel. Since 2015, the commitment to the Paris Agreement establishes the benchmark for political action. The assessments of mitigation costs can play a meaningful role in identifying the order of magnitude of the "price tag" on greenhouse gas emissions needed to achieve this common goal. Damage cost estimates on the other hand can provide useful insights on the cost of failing to achieve the temperature goal and for re-evaluating whether the set goal is ambitious enough.

Damage costs: influencing factors and assumptions

Damage models monetize climate impacts. A commonly used metric are the *social costs of carbon* (SCC). SCC are defined as the damages caused by the emission of an additional ton of CO_2. Despite considerable research effort conducted over the last decades on the economics and natural science of climate change, damage models still face **several severe limitations** at various dimensions calculating the SCC. Some limitations have been gradually improved upon, but the general issues remained largely unchanged since the early stages of their development. There exists thus in the literature no consensus on the order of magnitude — let alone the value — of the SCC.

In the following we list and categorize the major factors influencing the SCC.

Parts of the uncertainty stem from the underlying **scenarios and normative choices**. Those influencing factors can be chosen by policymakers. Subsequently, modelers have little discretion regarding implementation:

- The SCC increase for a **high-emission scenario**. This is because high emission lead to a high temperature increase and damages caused by the emission of an additional ton of CO_2 increase with the underlying temperature (convex damage function).

- The future GDP level is determined by the **socio-economic scenario** (mainly related to economic and population growth). Most damage models assume a steady GDP-growth, which is not affected by climate change. Climate damages are subsequently calculated as a fraction of the baseline GDP level. This has two major implications. First, future generations are assumed to be much richer (even accounting for climate damages), such that in a utilitarian setting the present generation ought to invest only little in climate mitigation. Correspondingly, assuming a higher GDP growth rate decreases the SCC. Second, a higher GDP growth rate increases the future GDP level, which leads to higher absolute damages. This increases the SCC and (partly) offsets the first effect. As GDP-growth rates differ among regions, those effects differ as well.

- The treatment of intergenerational equity boils down to the choice of the **discounting scheme and related parameters**. If the wellbeing of future generations is valued higher, the discount rate is lower and the SCC increase. There are essentially three discounting schemes: using a fixed discount rate, using a predetermined declining discount rate, or using Ramsey discounting (which combines fixed time-discounting with variable growth discounting). If Ramsey discounting is applied, several input parameters play a role: the pure rate of time preference, the economic growth rate (see previous bullet point), and intergenerational inequality aversion.

- Related to discounting is also the choice of the **time horizon** for modelling. If the chosen discount rate is high, damages in the far future become irrelevant to the SCC estimate. With a low discount rate on the other hand, a longer time horizon would also reflect damages in the far future and in particular slow-onset events such as Sea Level Rise. Choosing a longer time horizon thus only affects the SCC for a low discount rate.

- A related issue is the treatment of intragenerational equity (among people, nations or regions). Accounting for the equity within a generation essentially means that the valuation of damages in poorer countries is increased: In a utilitarian setting, a lower consumption level automatically implies a higher impact for a given damage (due to decreasing marginal utility of consumption). In addition, some models correct for the feature that low GDP levels entail low monetized damages. Those effects are accounted for in the **equity weighting** scheme. The impact of equity weighting on the SCC also depends on the region the results are normalized upon. If normalization is with respect to a rich region, the SCC increases.

- **Risk management choices** are relevant in a non-deterministic setting. Climate change may result in large damages, which have a major influence on cost estimates (especially if a high-risk aversion is assumed).

Another part of the uncertainty stems from **structural elements**. These influencing factors can be chosen by policymakers via the choice of the model(s) on which their decisions shall be based. Modelers have large discretion regarding implementation:

- The processes of the **climate system** translate emissions of greenhouse gases into geophysical impacts. Dedicated climate and earth system models comprise many components such as the carbon cycle, climate system responses (including extreme events), and sea-level rise. Those results can be used to calibrate in this respect much less complex damage models. Yet, even dedicated, sophisticated models feature large uncertainties. The most prominent aspect is the average temperature increase for a given amount of GHG emissions (metric climate sensitivity and related concepts). The larger the temperature increase the higher the SCC. There are, however, other important aspects of climate change, which are usually not explicitly included in damage models. Examples are changes in precipitation patterns or changes in the intensity and/or frequency of extreme events (such as floods, droughts, storms, etc.).

- Damage models need **damage functions** to translate geophysical impacts into monetary values. Damage functions can be clustered into three types: they are either (1) aggregate and highly stylized, (2) sector-specific enumerations, or (3) based on macro-econometric estimates. To provide an undistorted picture, a damage function ought to include impacts of all sectors affected by climate change as well as take into account regional differences and indirect effects. This is a tall order for all three damages function types. Especially for high temperature increases and long-term effects there exists little data on which one can base assumptions about future developments. Specification and calibration of damage functions thus remain in large parts ad-hoc. There is also the essentially unresolved debate whether climate change affects only the GDP-level or in addition the growth rate of GDP. The latter case leads to much higher damages in the long run as the growth effects accumulate.

- Damages can be decreased through **adaptation** efforts (*net* climate damages are the damages considering lowered impacts due to adaption plus the costs of adaptation). If damage models consider adaptation possibilities and related costs they do so either (1) implicitly and without costs as part of the socio-economic scenarios (which assume a certain resilience of societies and economies), (2) explicitly and entailing costs on an *aggregate* level, or (3) explicitly and entailing costs for *specific* sectors. The three approaches may also be used in parallel. The adaptability of future generations to a changing climate is essentially unknowable, as it depends on various aspects (e.g. technologies, governance, or resilience of societies) and large regional differences exist.
- If **technological change** is also modelled with respect to the costs of adaptation it has an impact on adaptation and thus net damage estimates.
- Only relevant for cost-benefit models (which consider damage and mitigation in parallel) is the difficulty to predict the scale and influence of future **abatement technologies and technological change.** This has a major influence on the mitigation costs and correspondingly on the endogenously determined emissions in cost-benefit models. This in turn influences the damages.

Finally, there are **exclusion choices**. The SCC can in principle be calculated without considering those influencing factors. Yet, we strongly recommend to only consider damage models for supporting climate policy that take them into account. Inclusion should thus be the default case and exclusion an explicit choice. Subsequently, modelers still have substantial discretion regarding the specific implementation.

- Damage models need to define an **approach to deal with uncertainties** of all the previously listed influencing factors. Uncertainty is present because of (1) the long time-horizon of the analysis, (2) understanding of crucial parts of the earth system (e.g. feedbacks or tipping points) is limited and (3) the economics to monetarize and aggregate impacts are contested. Early damage models have been run deterministically using ad-hoc assumptions and best-guess values of the uncertain parameters, largely neglecting uncertainties. It has become best practice, however, to run models stochastically. This allows to at least partly account for parametric and structural uncertainty. Unfortunately, the quantification of uncertainties remains incomplete and contested.
- Non-linearities and feedbacks in the climate system may cause climate change to trigger so-called "tipping points", which would cause parts of the earth and climate system to permanently switch to a new, large-scale state (e.g. collapse of polar ice sheets, breakdown of the oceanic thermohaline circulation, dieback of tropical forests, permanent changes of the monsoon circulation). Those low probability, high impact events may entail tremendous damages and are thus often referred to as **catastrophic climate change**. The related uncertainties are inherently difficult to account for, and especially so in the present setting

as they must be monetized. Damage functions thus treat catastrophic damages either not at all, incompletely or arbitrarily. Sometimes they are considered using an ad-hoc surcharge. Parts of the literature claim that the potential for catastrophe should be *the* essential driver for climate change policy in the spirit of an insurance approach. They thus call for limiting climate change to a certain threshold that shall not be crossed if the possibility of catastrophic damage is to be minimized.

- Climate change entails a variety of **non-market impacts**, which are either not directly connected to human wellbeing (e.g. biodiversity loss) or for which no direct market valuation exists (i.e. increased mortality). To provide a complete picture, it is important to account for those impacts. This is difficult, however, because non-market effects must be monetized and translated into the economic metrics of the damage models (e.g. GDP or total consumption). The corresponding methods are controversial and subject to great uncertainty (using e.g. the willingness to pay to prevent certain impacts or the statistical value of life).
- Finally, models ought to consider the limited substitutability between natural and market goods (e.g. using **ecological discounting**). There are various ways to extend the damage function accordingly, but data is scarce, and methods differ considerably.

Damage models — boiled down to the basics — model that emissions of greenhouse gases cause climate change, monetize the resulting biophysical impacts and aggregate those values across space and time. Each of those steps is connected with uncertainty and there are many degrees of freedom regarding the modelling approach. Consequently, developers of damage models have a considerable discretion to determine the SCC. By prescribing requirements for scenarios and (normative) choices as well as demanding obligatory extensions of the damage function, this discretion can be partly constrained by users.

An alternative way to derive SCC are expert elicitations (these studies either ask for SCC directly or deduce them from related answers). The results are as uncertain as those of models, since experts have little means to provide more robust answers than models. Moreover, many expert opinions will again be based on models.

Mitigation costs: influencing factors and assumptions

Mitigation cost models monetarise emission reduction costs. The literature uses **different concepts to measure mitigation costs**. Many mitigation models report the *carbon price* that, e.g., results from imposing a pre-defined mitigation target (for example a carbon budget). Under idealised conditions, the carbon price reflects **marginal abatement costs** (MAC), i.e. the costs of an incremental reduction in emissions by one unit.[1] However, as carbon prices only reflect the costs of abating the last und thus most expensive unit of emissions, they do not allow insights about the **total or average policy costs**. To measure the latter, models again use different cost metrics (the area under the MAC curve, change in (aggregate) consumption, change in Gross Domestic Product (GDP), additional total energy system costs or (additional) investment costs compared to a baseline scenario).

[1] It should be noted that the carbon price only equals marginal abatement costs under idealised and simplified assumptions. For example, if another environmental policy is already implemented, the carbon price will underestimate the true marginal abatement costs, as part of the emission reductions will be achieved by the other policy.

On the methodological side, there are a multitude of different models and underlying approaches assessing long-term transformation pathways and the resulting costs for given mitigation targets (cost-effectiveness-perspective). Generally, a **higher level of detail and complexity comes at the expense of the need for simplification in other regards**. Broadly, two main perspectives can be differentiated**.** The strength of a bottom-up perspective is the way it 'zooms in', presenting a high level of technical detail. In contrast, a top-down perspective aims to 'zoom out', presenting the 'big picture' including economy wide aspects. Complex mitigation cost models typically consist of a combination of different sub-models and may combine both perspectives (hybrid models).

Another dimension for model complexity is the **regional coverage**. Most prominent with respect to meta-studies analysing long-term mitigation pathways and associated mitigation costs (e.g., the IPCC assessment reports) are **global models.** The coarse temporal and spatial disaggregation of global models is often criticised for its limitations in representing real-world complexity and socio-political aspects as well as its limited usefulness for national level policy making. Therefore, a large range of country- and region-specific models exist as well. **EU or German national-level models** allow for a more detailed representation of country characteristics and heterogeneity. They are, however, less suitable for providing the 'big picture' and assessing global implications and decarbonisation interlinkages between regions as done in global models. Moreover, there are few available systematic (meta-)analyses of mitigation cost drivers on the regional level, while many global models regularly engage in model inter-comparison studies.

With the Paris Agreement acting as a political benchmark, the variety of existing mitigation cost estimates can be narrowed down by focusing on scenarios that are in line with the Paris Agreement. Nevertheless, the range of mitigation cost estimates remains large due to differences in underlying assumptions. These assumptions can be model-specific characteristics or can be parameters that can be varied for different model runs reflecting different scenarios. For the latter it is possible to (at least to a certain degree) harmonise these across models for inter-comparisons. All these elements feature normative (policy prescriptive) components as well as scientific uncertainty and technical limitations. Model-specific factors further may be differentiated into structural elements and elements we call exclusion/inclusion choices.

The most relevant **scenario assumptions** are:

- **Socio-economic narratives** (e.g., the Shared Socio-economic Pathways (SSPs)) are storylines outlining assumptions about (potential) socio-economic developments (including economic development, population, lifestyles, 'ease' of technology diffusion, regional rivalry) and thus reflect the level of challenges for mitigation. Unsurprisingly, SSPs with higher mitigation challenges lead to higher mitigation costs or even infeasibility issues for very ambitious mitigation targets.
- **Baseline assumptions** define counterfactual future developments in the absence of (additional) climate policy and are strongly related to the socio-economic narratives above.
- To reflect the inherent political economy uncertainty of future scenarios and to challenge the common assumption in global models of a uniform global carbon price with quasi-immediate implementation, studies have assessed the impact of several alternative **policy assumptions**. Fragmented action (i.e., no global cooperation) typically increases mitigation costs. Likewise, if emissions from certain sectors such as land-use are assumed to not be

covered by carbon pricing for practical reasons higher carbon prices in other sectors need to compensate for this. Also, a delay in climate action increases mitigation costs substantially in both global and regional (EU) models, partly leading to infeasibility or prohibitively high carbon prices.

The implementation of assumptions that vary between pathways is also related to various **normative (policy prescriptive) choices.** The most relevant are:

- The **emissions or temperature limit** is an important normative choice, with the Paris Agreement providing a clear benchmark since 2015. Together with the net-zero greenhouse gas mitigation goal expressed in Article 4, Article 2.1 defines a long-term temperature limit of "well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels". However, this formulation leaves room for interpretation about whether and to what degree Article 2.1 allows for limited overshoot of the 1.5°C long-term temperature limit. Thus, two additional normative choices result: First, whether **temporary overshoot** of the target is allowed as long as the limit is met, for example, by the end of the century and if yes how much overshoot. Depending on the allowed overshoot, two scenarios labelled '1.5°C' may refer to very different peak mean global temperature changes and associated climate damages. Second, choosing a higher **probability to remain below the defined temperature limit** is associated with a more ambitious target and lower expected damages as well. The probability reflects remaining scientific uncertainties related to the carbon cycle and translating emission levels to temperature changes. Scenarios allowing for high overshoot in combination with high discount rates typically shift the mitigation burden into the future and yield lower carbon prices in earlier years at the expense of steeply increasing carbon prices towards the end of the century (especially in intertemporal optimisation models).
- **Regional distribution of costs and burden sharing:** Global models frequently assume that mitigation is carried out where it is cheapest globally, disregarding political realities and aspects such as historical responsibility or who pays for mitigation. To account for this, global models can impose various burden sharing schemes to distribute mitigation efforts between regions or countries, with limited agreement on which scheme can be considered 'fair'. In reality, the distribution of mitigation activity between regions is unlikely to follow these chosen idealised setting, therefore likely leading to higher mitigation costs. Moreover, many global models 'freeze' the current global unequal income patterns to avoid model-driven large financial transfers and income redistribution in the model results.
- **Discounting (scheme and parameter choice):** While in mitigation models the discount rate does not affect the (pre-defined) mitigation target choice per se, it has a direct impact on i) the transformation pathway over time, ii) the technology mix and iii) the amount of overshoot and thus the associated damages. Discounting has strong implications for intergenerational justice, as higher discount rates shift mitigation efforts and costs into the future. This is especially relevant, for example, for large-scale deployment of (costly) technologies such as negative emission technologies. In the current literature, commonly found discount rates in mitigation cost models are around 5% but often lack transparency. In

contrast to the literature on the Social Costs of Carbon, the role of the discount rate choice in mitigation cost models is rarely discussed, and sensitivity analyses are scarce.

- Modelers typically have large discretion over how they implement techno-economic assumptions in the form of **constraints on technology options,** for example for implementing socio-economic narratives:
  - These constraints can be related to **restricting the use of certain technologies** to reflect low public acceptance (e.g. nuclear or Carbon Capture and Storage (CCS)) or sustainability concerns (e.g. bioenergy with CCS). The exclusion of cost-competitive technology options typically increases mitigation costs. The exclusion or restriction of negative emission technologies (NETs) have implications for the intertemporal distribution of efforts and costs as lower near-term efforts cannot be compensated by negative emissions in the second half of the century, increasing near-term mitigation costs. Moreover, several recent developments in new technologies, such as hydrogen or Direct Air Capture, have yet remained underrepresented in many (global) mitigation models.
  - Imposed model constraints may also **limit the speed of phasing out conventional (carbon intensive) technologies** or **scaling up new (low carbon) technologies**. Compared to observed developments, global mitigation models have typically overestimated the future technology costs of renewable energy technologies (like wind and solar) and underestimated their growth rates. This has implications for the resulting technology mix which can be policy prescriptive. If the speed of phasing out fossil technologies is assumed to be low, more CCS and negative emission technologies are needed to compensate for a slower transition. More favourable assumptions on the diffusion of renewable energy technologies typically decrease mitigation costs, especially in combination with endogenous technological change.

Structural elements are characterising the inherent model set-up choices. Important structural elements of mitigation cost models are:

- **Economic system representation and equilibrium type:** Frequently used models include i) bottom-up Partial Equilibrium (energy system) models ii) General Equilibrium Optimal Growth models featuring a simplified representation of the whole economic system and iii) Computable General Equilibrium (CGE) models featuring a detailed representation of sector interlinkages. All these model types assume some form of equilibrium and optimisation process. However, it should be noted that starting from the assumption that the economy is in equilibrium before introducing climate policy by definition imposes macro-economic costs resulting from climate policy (deviation from equilibrium). This reflects a certain world view, which is challenged by models that represent pre-existing inefficiencies (e.g., so far less frequently used 'non-equilibrium models') in which climate policy can even lead to economic gains. Mitigation costs tend to be higher in General Equilibrium models compared to Partial Equilibrium models as the latter typically disregard feedback effects and implementation barriers for the wider economy. Higher costs in CGE models compared to Optimal Growth models are related to CGE models' better representation of interactions between sectors and economy-wide distortion as well as differences in the foresight mechanism typically applied in those model types.

- **Perfect foresight vs. myopic expectations:** The two main types to consider future information: i) myopic expectations, which are typically applied by CGE models or ii) perfect foresight, a forward-looking approach optimising over the time horizon, typically applied by Optimal Growth models. The myopic approach assumes more 'short-sighted' actors taking investment decisions based on information available in the respective period without knowing the future. Perfect foresight models in contrast take a long-term forward-looking planning perspective on what would be intertemporally optimal, assuming perfect information about future costs. Perfect foresight (Optimal Growth) models tend to yield lower carbon prices – at least in the shorter run – compared to myopic (CGE) models. This is because assuming perfect foresight allows for a more efficient allocation of emission reductions over time. Moreover, Optimal Growth models typically abstract distortions or interaction effects between sectors which are a feature of CGE models. However, perfect foresight (Optimal Growth) models typically exhibiting exponentially increasing carbon prices over time leading to comparatively higher long-run carbon prices.
- **Technological change (TC)**: Broadly, models can be grouped into those where TC is exogenous and those that model TC endogenously (e.g. through 'learning by doing'). Models which assume perfect foresight supplemented with endogenous TC tend to find lower aggregated mitigation costs. Endogenous TC tends to incentivise earlier investments in low-carbon technologies thus increasing mitigation costs in the shorter term but reducing costs for future periods.
- **Coverage of greenhouse gases (GHGs):** While CO_2 is dominant for the energy sector, non-CO_2 GHGs play an important role in other sectors like agriculture, sewage treatment, or industrial processes. A multi-gas approach allows for more flexibility in mitigation, thus reducing costs at least in the short term, as some non-CO_2-abatement options are comparably cheap (e.g. nitrous oxide destruction in industrial processes). However, in other sector mitigation of non-CO_2 gases is more challenging (e.g. methane emissions from livestock or nitrous oxide emissions from fertiliser use), which is a major challenge for reaching zero emissions in the long run.

Elements we would consider **'exclusion/inclusion choices'** are elements of a model that may be included or excluded in different model versions but still represent some form of structural modules characterising the model:

- Various types of positive (or negative) **side-effects of mitigation action** may be taken into account within the models when assessing mitigation costs, such as trade-offs with food security or health benefits from reduced air pollution. This requires the monetarisation of such (often non-monetary) side effects involving value judgements. Several studies accounting, for example, for health co-benefits find that these could partly or even fully outweigh mitigation costs in certain regions.

- **Representation of options for mitigation:** Some models account for policy instrument design such as efficiency standards or subsidies for specific (low carbon) technologies. The analysis of these kinds of policies typically plays an important role in regional or national models, in which a carbon price is often not the main driver of emission reductions. Furthermore, in global studies, Low-Energy-Demand scenarios highlight the role of so-called demand side mitigation options and show that changes in consumption patterns towards more sustainable lifestyles (e.g., reduced electricity use, dietary changes) can substantially reduce mitigation costs and also reduce the need for negative emission technologies.
- Models may represent **'real-world' imperfections** such as market barriers, either as part of the model set-up or as, for example, cost-mark ups. Pre-existing inefficiencies allow for negative cost options, but market barriers can also increase mitigation costs.

Relevance of climate cost models for climate policy

Mitigation and damage cost models are complex, incorporating assumptions on numerous influencing factors and results are thus prone to uncertainty. Therefore, a correct interpretation of the results requires a sound understanding of the models' assumptions and influencing factors. Results should never be taken at "face value" or as accurate predictions of future outcomes. While this is true in general for all types of models, this is especially relevant in the context of climate cost modelling. The long-term horizon of climate change, the inertia of the involved systems as well as the complex interplay of socio-economic, behavioural and physical aspects related to climate change makes the uncertainty severe and multi-dimensional.

Many scholars thus reason that the main contribution of mitigation and damage cost models is not to provide exact numbers but insights: they are a coherent and consistent way to scrutinise complex issues and to make assumptions and approaches transparent. They are also a tool to facilitate risk management with respect to future damages and mitigation costs.

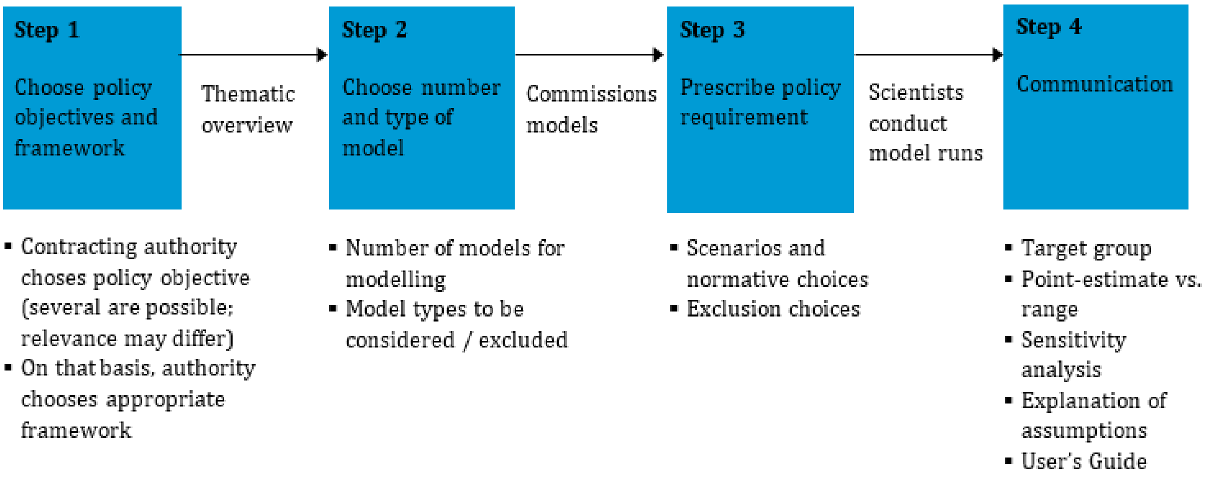
Yet, a price tag on GHG emissions is a crucial part of any climate policy. In the current public debates, the costs and economic impacts of policy choices are a central element to appreciate the relevance of a political issue. Even if uncertainty is high, having science-based estimates of climate costs is key for political decision making. Providing a price tag is thus mandatory even though there is no clear scientific agreement on its appropriate value. It is however important to properly communicate on the uncertainties in relation to model estimates and to allow for a structured discussion on key influencing factors.

Seen from a wider perspective, while a price tag on carbon is key, it is but one of many elements that a comprehensive climate policy requires. In this wider context mitigation models play a further role: Their primary goal is often to identify and analyse economically or technically optimal system transformation pathways, while the resulting mitigation costs are secondary information. This is especially true for national mitigation models, which identify political fields of action, describe additional investment needs and allow to design a consistent and cost-efficient emission reduction strategy.

A guidance in four steps to derive climate cost estimates

We propose a four-step process to derive climate costs as depicted in the following figure. We strictly focus on the *process* and do not recommend specific values or ranges for the involved parameters or results.

Figure B: The 4 Steps for a contacting authority to provide information on climate costs



Source: own illustration, Infras

In Step 1, the contracting authority defines the framework based on its policy objectives. In Step 2, the contracting authority chooses models to derive climate cost estimates. This choice concerns both the number of models as well as the model-type(s). It may also commission models to run specific analyses. In Step 3, the contracting authority prescribes policy requirements for certain categories of influencing factors. These requirements will decrease the literature's uncertainty range to a certain extent. The remaining range primarily stems from scientific and scenario uncertainty. Finally, in Step 4, the contracting authority uses the model results to communicate estimates of climate costs. This entails a fundamental tradeoff between simplicity and scientific comprehensiveness. Users are primarily interested in easy-to-use numbers. At the same time the caveats, as discussed above, should be conveyed to the user in an appropriate way.

Zusammenfassung

Hintergrund und Ziele der Studie

Der Klimawandel ist eine der größten Herausforderungen, vor denen die Menschheit derzeit steht. Er wird zu erheblichen Schäden führen, selbst wenn er auf einen Anstieg der globalen Mitteltemperatur um 1,5°C gegenüber dem vorindustriellen Niveau beschränkt bleibt. Ohne große Anstrengungen zur Reduktion von Treibhausgasen werden die Schäden noch höher ausfallen. Es ist wichtig, das Ausmaß der Schäden zu bewerten, um die politische und öffentliche Unterstützung für ehrgeizige Klimaschutzmaßnahmen zu stärken. Die aktuelle Methodenkonvention 3.0 des Umweltbundesamtes empfiehlt daher für Treibhausgasemissionen im Jahr 2016 einen Kostensatz von 180 $€_{2016}/tCO_{2eq}$ und eine Sensitivitätsanalyse mit 640 $€_{2016}/tCO_{2eq}$. Diese Zahlen basieren auf dem Modell FUND, das Schäden für heutige und zukünftige Generationen berechnet und aggregiert. Ihr Wert hängt von Annahmen zu verschiedenen Einflussfaktoren ab. So ergibt sich der Unterschied der obigen Zahlen allein aus der Annahme zur reinen Zeitpräferenzrate (ein entscheidender Teil des Diskontierungssatzes) von 1% bzw. 0%. Für diese und andere Einflussfaktoren gibt es auf wissenschaftlicher, wirtschaftlicher, sozialer und politischer Ebene eine anhaltende Debatte über die angemessene Wahl. Folglich weichen Schätzungen von Klimaschäden in der wissenschaftlichen Literatur erheblich voneinander ab.

Das Umweltbundesamt definiert in der Methodenkonvention 3.0 "Klimakosten" als Schadenskosten. Dies liegt daran, dass der Fokus der Methodenkonvention auf externen Schäden liegt. Ein alternativer Ansatz "Klimakosten" herzuleiten, sind Vermeidungskosten. Dies sind die Kosten, um ein bestimmtes Ziel für die Reduktion von Treibhausgasemissionen zu erreichen. In der Regel werden die Ziele des Pariser Abkommens verwendet, in dem sich die Länder darauf geeinigt haben, den Anstieg der globalen Mitteltemperatur auf "deutlich unter 2°C über dem vorindustriellen Niveau zu begrenzen und die Bemühungen zur Begrenzung des Temperaturanstiegs auf 1,5°C fortzusetzen". Auch Schätzungen der Vermeidungskosten sind mit großen Unsicherheiten behaftet. Einige Herausforderungen sind dabei die gleichen wie bei den Schadenskosten (z.B. der Diskontsatz), andere sind spezifisch für Vermeidungskosten (z.B. Einschränkungen bestimmter Technologieoptionen).

Wie die folgende Tabelle zeigt, hängt die Wahl des geeigneten konzeptionellen Rahmens vom politischen Ziel ab.

Tabelle A: Politische Ziele und der geeignete konzeptuelle Rahmen

#	Politisches Ziel	Anmerkungen	Politische Relevanz
Schadenskosten sind der geeignete konzeptuelle Rahmen			
D1	**Das Bewusstsein für Klimaschäden schärfen, falls die Politik nicht handelt**	**Bezogen auf "Kosten der Untätigkeit"**	**Hoch**
D2	**Internalisierung externer Kosten nach dem Verursacherprinzip**	**Mittels einer Steuer/Abgabe oder anderer marktbasierter Instrumente; starke Verbindung zur Definition von SCC**	**Hoch**
D3	Monetarisierung (vermiedener) Klimaschäden im Zusammenhang mit bestimmter Maßnahme oder politischem Instrument	Input für Kosten-Nutzen-Analyse, Bewertung oder Folgenabschätzung einer Politik	Mittel
D4	Nutzen einer bestimmten Anpassungsmaßnahme ermitteln	Sektorspezifische, lokale Schäden erforderlich	Gering
Vermeidungskosten sind der geeignete konzeptuelle Rahmen			
M1	**Identifizieren des erforderlichen Aufwands (z.B. Kohlenstoffsteuer/-abgabe), um innerhalb einer vordefinierten Temperaturgrenze zu bleiben**	**Das Übereinkommen von Paris definiert international vereinbarte Temperaturgrenzen**	**Hoch**
M2	Bereitstellen eines Maßstabs für gesellschaftlich wertvolle Vermeidungsmaßnahmen (privat und öffentlich) und politische Instrumente	Entspricht dem französischen Ansatz ("Sozialer Wert von Vermeidungsmaßnahmen")	Mittel
M3	Schätzen Sie die (Gesamt-)Kosten für das Erreichen eines vordefinierten Minderungsziels	Zur Berechnung der Gesamtkosten werden die Grenzkosten (MAC-Kurve) oder die durchschnittlichen Vermeidungskosten benötigt	Mittel
M4	Abschätzung der Vermeidungskosten im Zusammenhang mit einer bestimmten Maßnahme oder politischem Instrument	Input für Kosten-Nutzen-Analyse, Bewertung oder Folgenabschätzung einer Politik	Mittel
Beide konzeptuelle Rahmen können verwendet werden			
B1	Bereitstellung von Informationen für interne Schattenpreise von Unternehmen	Unternehmen können beide konzeptuelle Rahmen verwenden	Mittel
B2	Bereitstellung eines Referenzwertes für den Preis von Emissionsgutschriften in resultatbasierten Finanzierungssystemen (z.B. Artikel 6.4 des Übereinkommens von Paris)	Der Preis wird in der Regel durch Angebot und Nachfrage bestimmt; der Auftraggeber kann jedoch einen Richtwert oder einen Festpreis angeben	Gering

Quelle: eigene Darstellung, Infras und Climate Analytics

Vor diesem Hintergrund verfolgt die vorliegende Studie die folgenden Ziele:

- Bereitstellung eines umfassenden Überblicks über die Literatur zu Klimakosten (Schadenskosten und Vermeidungskosten).
- Analyse der Bedeutung und der Auswirkungen verschiedener Einflussfaktoren und Annahmen für Schätzungen der Schadenskosten und Vermeidungskosten.
- Erstellung einer Typologie dieser Einflussfaktoren und Annahmen.
- Identifizierung der relevanten Politikziele, um Informationen über die Klimakosten bereitzustellen.
- Empfehlung eines Verfahrens zur Quantifizierung der Klimakosten für zukünftige Methodenkonventionen des Umweltbundesamtes.

Zwei konzeptionelle Rahmen zur Ableitung von Klimakosten

Schadenskosten und Vermeidungskosten sind die zwei konzeptionellen Rahmen zur Ableitung von Klimakosten. Die folgende Tabelle erläutert die grundlegenden Unterschiede und die Anwendungsbereiche. Schadenskosten und Vermeidungskosten können auch parallel betrachten. Diese Herangehensweise steht jedoch aus methodischen Gründen nicht im Mittelpunkt der vorliegenden Studie.

Tabelle B: Rahmenwerke zur Ableitung von Klimakosten

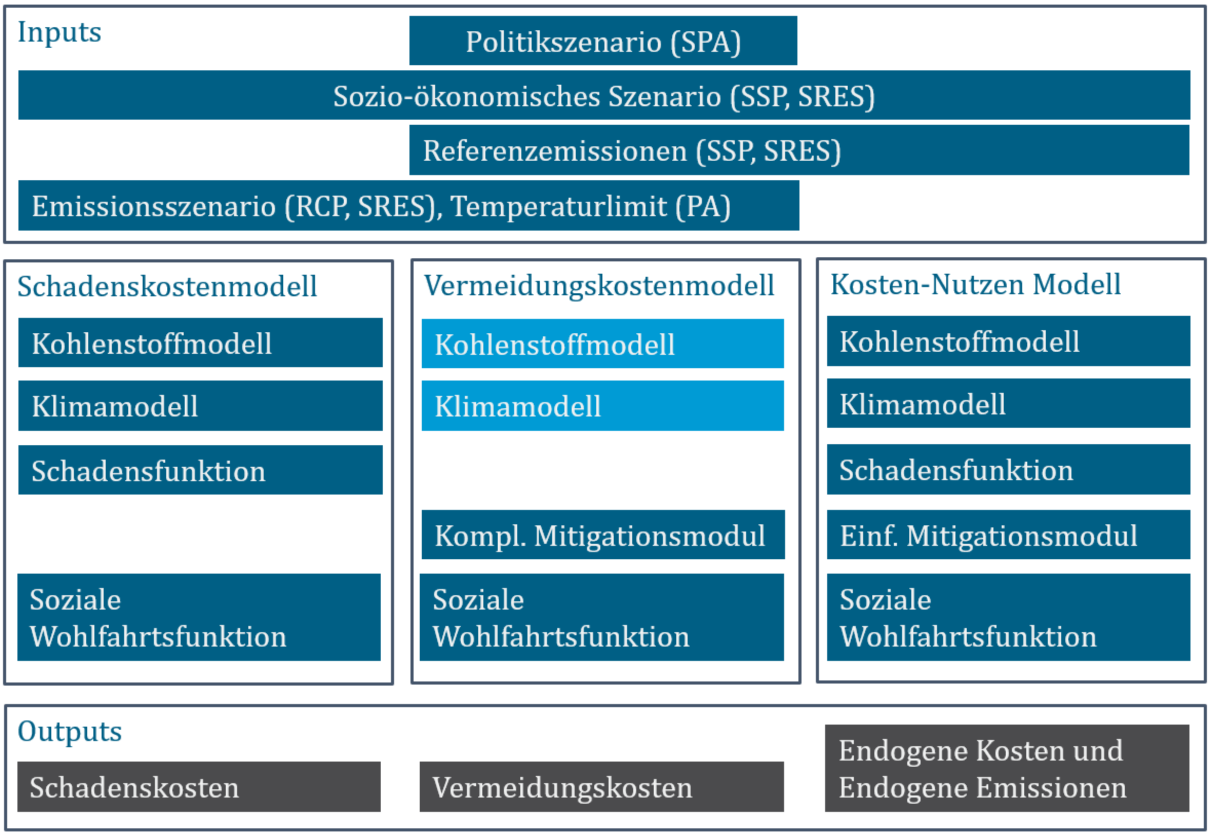
	Schadenskosten	Vermeidungskosten
Erläuterung	• Beziehen sich auf die verschiedenartigen Schäden, die durch die Emission von Treibhausgasen verursacht werden • Beinhalten Anpassungskosten • Häufig ausgedrückt als „social costs of carbon“ (SCC) • SCC sind als Grenzkosten definiert, aber Schadenskosten können auch als Gesamt- oder Durchschnittskosten berechnet werden • SCC steigen normalerweise, bei einem höheren zugrundeliegende Emissionspfad • Abgedeckt in Teil 2 dieses Berichts	• Resultieren aus der Umsetzung von Maßnahmen zur Emissionsminderung • Können Nebennutzen beinhalten (z.B. saubere Luft) • Mehrere Berechnungsansätze: gesamtwirtschaftliche Grenz-, Durchschnitts- oder Gesamtkosten im Vergleich zu einem Referenzszenario • Bezieht sich auf bestimmte Maßnahmen, bestimmte Sektoren oder die gesamte Wirtschaft • Steigen mit ambitionierteren Reduktionsanstrengungen • Abgedeckt in Teil 3 dieses Berichts
Anwendbarkeit (Beispiele)	• Internalisierung externer Kosten ("Verursacherprinzip"-Prinzip) • Nutzen in Form von vermiedenen Schäden bei der Durchführung einer Kosten-Nutzen-Analyse einer Politik oder einer spezifischen Massnahme	• Angemessener Steuersatz zur Erreichung eines vordefinierten Minderungsziels (insgesamt oder für einen bestimmten Sektor) • Kosten einer bestimmten Politik

Quelle: eigene Darstellung, Infras

Die folgende Abbildung veranschaulicht die Inputs und Outputs der Modelle, die diese konzeptionellen Rahmen verwenden. Modell-Inputs sind verschiedene Arten von Szenarien. Die

Modelle bestehen aus verschiedenen Modulen und die Outputs sind die resultierende Kostenschätzung (in grau).

Abbildung A: Inputs und Module verschiedener Arten von Klimakostenmodellen



Quelle: eigene Darstellung, Infras

Die Abbildung zeigt, dass es einen dritten konzeptionellen Rahmen gibt. Kosten-Nutzen-Modelle betrachten Schadens- und Vermeidungskosten parallel und sind damit in der Lage, Emissionen endogen zu bestimmen (d.h. sie bestimmen einen — je nach Modell — "optimalen" Emissionspfad). Dies steht jedoch nicht im Fokus der vorliegenden Studie, da diese Methode konzeptionell problematisch ist. Zudem stellt das Pariser Abkommen einen internationalen politischen Konsens dar, und der entsprechende Emissionspfad ist somit ein logischer Bezugspunkt. Die Bestimmung eines anderen Emissionspfads mit Hilfe von Kosten-Nutzen-Modellen, deren Ergebnisse sehr stark von den Modellannahmen abhängen, bringt wenig Mehrwert.

Es kann nichtsdestotrotz sinnvoll sein, Schadens- und Minderungskosten parallel zu betrachten. Seit 2015 stellt die Verpflichtung zum Pariser Abkommen den Maßstab für politisches Handeln dar. Die Bewertungen der Vermeidungskosten können eine sinnvolle Rolle bei der Bestimmung der Größenordnung des "Preisschildes" für Treibhausgasemissionen spielen, das zur Erreichung dieses gemeinsamen Ziels erforderlich ist. Die Schadenskostenschätzung hingegen kann nützliche Erkenntnisse über die Kosten des Verfehlens des Temperaturziels liefern sowie für die Neubewertung der Frage, ob das gesetzte Ziel ehrgeizig genug ist.

Schadenskosten: Einflussfaktoren und Annahmen

Schadensmodelle monetarisieren Klimaauswirkungen. Eine häufig verwendete Metrik sind die *sozialen Kosten von Kohlenstoff* („social costs of carbon"; SCC). Die SCC sind definiert als die Schäden, welche durch den Ausstoß einer zusätzlichen Tonne CO_2 verursacht werden. Trotz der beträchtlichen Forschungsanstrengungen, die in den letzten Jahrzehnten auf dem Gebiet der Ökonomie und Naturwissenschaft des Klimawandels unternommen wurden, stoßen Schadensmodelle bei der Berechnung des SCC in verschiedenen Dimensionen immer noch auf **mehrere gravierende Einschränkungen**. Einige Einschränkungen wurden nach und nach verbessert, aber die allgemeinen Fragen sind seit den frühen Phasen ihrer Entwicklung weitgehend unverändert geblieben. Es besteht daher in der Literatur kein Konsens über die Größenordnung — geschweige denn den Wert — der SCC.

Im Folgenden listen und kategorisieren wir die wichtigsten Faktoren, die die SCC beeinflussen.

Teile der Unsicherheit ergeben sich aus den zugrunde liegenden **Szenarien und normativen Entscheidungen**. Diese Einflussfaktoren können von den politischen Entscheidungsträgern ausgewählt werden. Modellierer haben danach nur wenig Ermessensspielraum hinsichtlich der Umsetzung:

- Die SCC steigen für ein **Szenario mit hohen Emissionen**. Diese führen zu einem hohen Temperaturanstieg. Und Schäden, die durch die Emission einer zusätzlichen Tonne CO_2 verursacht werden, erhöhen sich mit der zugrunde liegenden Temperatur (konvexe Schadensfunktion).

- Das zukünftige BIP-Niveau wird durch das **sozioökonomische Szenario** bestimmt (hauptsächlich im Zusammenhang mit dem Wirtschafts- und Bevölkerungswachstum). Die meisten Schadensmodellen nehmen ein stetiges BIP-Wachstum an, das nicht durch den Klimawandel beeinflusst wird. Klimaschäden werden anschließend als ein Bruchteil des Ausgangsniveaus des BIP berechnet. Dies hat zwei wesentliche Auswirkungen. Erstens wird davon ausgegangen, dass künftige Generationen wesentlich reicher sein werden (auch unter Berücksichtigung der Klimaschäden), so dass die heutige Generation in einem utilitaristischen Rahmen nur wenig in den Klimaschutz investieren sollte. Dementsprechend verringert die Annahme einer höheren BIP-Wachstumsrate die SCC. Zweitens erhöht eine höhere BIP-Wachstumsrate das zukünftige BIP-Niveau, was zu höheren absoluten Schäden führt. Dies erhöht die SCC und gleicht (teilweise) den ersten Effekt aus. Da sich die BIP-Wachstumsraten von Region zu Region unterscheiden, sind auch diese Effekte unterschiedlich.

- Die Behandlung der intergenerationellen Gerechtigkeit schlägt sich in der Wahl des **Diskontierungsschemas und der damit verbundenen Parameter** nieder. Wenn das Wohlergehen künftiger Generationen höher bewertet wird, ist der Diskontsatz niedriger und die SCC steigen. Es gibt im Wesentlichen drei Diskontierungsschemata: die Verwendung eines fixen Diskontsatzes, die Verwendung eines prädeterminiert sinkenden Diskontsatzes oder die Verwendung der Ramsey-Diskontierung (die eine feste zeitliche Diskontierung mit einer variablen Wachstumsdiskontierung kombiniert). Bei der Anwendung der Ramsey-Diskontierung spielen diverse Inputparameter eine Rolle: die reine Zeitpräferenzrate, die BIP-Wachstumsrate (siehe vorheriger Aufzählungspunkt) und die Aversion gegen intergenerationelle Ungleichheit.

- Im Zusammenhang mit der Diskontierung steht auch die Wahl des **Zeithorizonts** für die Modellierung. Wenn der gewählte Diskontsatz hoch ist, werden Schäden in der fernen Zukunft für die SCC-Schätzung irrelevant. Bei einem niedrigen Diskontsatz hingegen würde ein längerer Zeithorizont auch Schäden in der fernen Zukunft widerspiegeln (insbesondere langsam einsetzende Ereignisse wie den Meeresspiegelanstieg). Die Wahl eines längeren Zeithorizonts wirkt sich daher nur bei einem niedrigen Diskontsatz auf die SCC aus.

- Ein verwandtes Thema ist die Behandlung der intragenerationellen Gerechtigkeit (zwischen Menschen, Nationen oder Regionen). Die Berücksichtigung der Gerechtigkeit innerhalb einer Generation bedeutet im Wesentlichen, dass die Bewertung von Schäden in ärmeren Ländern erhöht wird: In einem utilitaristischen Rahmen bedeutet ein niedrigeres Konsumniveau automatisch eine höhere Auswirkung für einen gegebenen Schaden (aufgrund des abnehmenden Grenznutzens des Konsums). Darüber hinaus korrigieren einige Modelle, dass ein niedriges BIP-Niveau zu geringen monetarisierten Schäden führt. Diese Auswirkungen werden im „**equity weighting**" Schema berücksichtigt. Die Auswirkungen des equity weighting auf die SCC hängen auch von der Region ab, für die die Ergebnisse normiert werden. Erfolgt die Normierung in Bezug auf eine reiche Region, steigt der SCC.

- **Risikomanagemententscheidungen** sind in einem nicht-deterministischen Umfeld relevant. Der Klimawandel kann zu großen Schäden führen, die einen großen Einfluss auf die Kostenschätzungen haben (besonders wenn man eine hohen Risikoaversion annimmt).

Ein anderer Teil der Unsicherheit ist auf **strukturelle Elemente** zurückzuführen. Diese Einflussfaktoren können von den politischen Entscheidungsträgern über die Wahl des Modells bzw. der Modelle gewählt werden, auf denen ihre Entscheidungen beruhen sollen. Modellierer haben einen großen Ermessensspielraum bei der Umsetzung:

- Die Prozesse des **Klimasystems** übersetzen Emissionen von Treibhausgasen in geophysikalische Auswirkungen. Spezielle Klima- und Erdsystemmodelle umfassen viele Komponenten wie den Kohlenstoffkreislauf, Reaktionen des Klimasystems (einschließlich Extremereignisse) und den Anstieg des Meeresspiegels. Diese Ergebnisse können dazu verwendet werden, in dieser Hinsicht weit weniger komplexe Schadensmodelle zu kalibrieren. Doch selbst dedizierte, hochentwickelte Modelle weisen große Unsicherheiten auf. Der prominenteste Aspekt ist der durchschnittliche Temperaturanstieg bei einer bestimmten Menge von Treibhausgasemissionen (Zusammengefasst in der Metrik „Klimasensitivität" oder verwandte Konzepte). Je größer der Temperaturanstieg, desto höher die SCC. Es gibt jedoch noch andere wichtige Aspekte des Klimawandels, die in der Regel nicht explizit in Schadensmodelle einbezogen werden. Zum Beispiel Änderungen der Niederschlagsmuster oder Änderungen der Intensität und/oder Häufigkeit von Extremereignissen (wie Überschwemmungen, Dürren, Stürme usw.).

- Schadensmodelle benötigen **Schadensfunktionen**, um geophysikalische Auswirkungen in monetäre Werte zu übersetzen. Schadensfunktionen lassen sich in drei Typen gruppieren: Sie sind entweder (1) aggregiert und stark stilisiert, (2) sektorspezifische Aufzählungen oder (3) basieren auf makroökonometrischen Schätzungen. Um ein unverzerrtes Bild zu erhalten, sollte eine Schadensfunktion die Auswirkungen aller vom Klimawandel betroffenen

Sektoren umfassen sowie regionale Unterschiede und indirekte Effekte berücksichtigen. Dies ist für alle drei Schadensfunktionstypen eine hohe Anforderung. Insbesondere für hohe Temperaturanstiege und Langzeiteffekte gibt es nur wenige Daten, auf die man Annahmen über zukünftige Entwicklungen stützen kann. Die Spezifikation und Kalibrierung von Schadensfunktionen bleibt daher in weiten Teilen ad-hoc. Hinzu kommt die im Wesentlichen ungeklärte Debatte, ob der Klimawandel nur das BIP-Niveau oder zusätzlich die Wachstumsrate des BIP beeinflusst. Letzterer Fall führt langfristig zu wesentlich höheren Schäden, da sich die Wachstumseffekte kumulieren.

- Schäden können durch **Anpassung** an den Klimawandel verringert werden (Nettoklimaschäden sind die Schäden unter Berücksichtigung der durch die Anpassung verringerten Auswirkungen zuzüglich der Kosten der Anpassung). Wenn Schadensmodelle Anpassung und die damit verbundenen Kosten berücksichtigen, tun sie dies entweder (1) implizit und ohne Kosten als Teil der sozio-ökonomischen Szenarien (welche eine bestimmte Widerstandsfähigkeit der Gesellschaft und Wirtschaft zugrunde legen), (2) explizit und mit Kosten auf *aggregierter* Ebene oder (3) explizit und mit Kosten für *bestimmte* Sektoren. Teils werden diese drei Ansätze auch parallel verwendet. Die Anpassungsfähigkeit zukünftiger Generationen an ein sich veränderndes Klima ist im Wesentlichen nicht bekannt, da sie von verschiedenen Aspekten abhängt (z.B. Technologien, Governance oder Widerstandsfähigkeit von Gesellschaften) und große regionale Unterschiede bestehen.

- Wenn **der technologische Wandel** auch im Hinblick auf die Anpassungskosten modelliert wird, wirkt er sich auf die Anpassung und damit auf die Netto-Schadensschätzungen aus.

- Nur für Kosten-Nutzen-Modelle (welche Schäden und Schadensminderung parallel betrachten) ist die Schwierigkeit relevant, das Ausmaß und den Einfluss zukünftiger **Vermeidungstechnologien und des technologischen Wandels** vorherzusagen**.** Dies hat einen großen Einfluss auf die Vermeidungskosten und dementsprechend auf die endogen bestimmten Emissionen in Kosten-Nutzen-Modellen. Dies wiederum beeinflusst die Schäden.

Schließlich gibt es noch **Ausschlussmöglichkeiten**. Die SCC können im Prinzip ohne Berücksichtigung dieser Einflussfaktoren berechnet werden. Wir empfehlen jedoch dringend, nur solche Schadensmodelle zur Unterstützung der Klimapolitik zu berücksichtigen, die diese berücksichtigen. Eine Berücksichtigung sollte daher der Standardfall sein und ein Ausschluss eine explizite Wahl. In der Folge haben die Modellierer noch erheblichen Ermessensspielraum hinsichtlich der konkreten Umsetzung.

- Schadensmodelle müssen einen **Ansatz für den Umgang mit den Unsicherheiten** aller zuvor aufgeführter Einflussfaktoren definieren. Unsicherheit herrscht vor, wegen (1) dem langen Zeithorizont der Analyse, (2) weil das Verständnis der entscheidenden Teile des Erdsystems (z.B. Rückkopplungen oder Kipppunkte) begrenzt ist und (3) weil die wirtschaftlichen Methoden zur Monetarisierung und Aggregierung der Auswirkungen umstritten ist. Frühe Schadensmodelle wurden deterministisch unter Verwendung von ad-hoc-Annahmen und best-guess Schätzwerten der unsicheren Parameter durchgeführt, wobei Unsicherheiten weitgehend vernachlässigt wurden. Es hat sich jedoch als besten Praxis herausgestellt, Modelle stochastisch zu betreiben. Dies erlaubt es, parametrische und strukturelle Unsicherheit zumindest teilweise zu berücksichtigen. Leider bleibt die Quantifizierung von Unsicherheiten unvollständig und umstritten.

- Nichtlinearitäten und Rückkopplungen im Klimasystem können dazu führen, dass durch den Klimawandel so genannte "Kipp-Punkte" ausgelöst werden, die dazu führen, dass Teile der Erde und des Klimasystems permanent in einen neuen, großräumigen Zustand übergehen (z.B. Kollaps der polaren Eisschilde, Zusammenbruch der ozeanischen thermohalinen Zirkulation, Absterben von Tropenwäldern, permanente Veränderungen der Monsunzirkulation). Diese Ereignisse mit geringer Wahrscheinlichkeit und hohen Auswirkungen können enorme Schäden nach sich ziehen und werden daher oft als **katastrophaler Klimawandel bezeichnet**. Die damit verbundenen Unsicherheiten sind von Natur aus schwer zu berücksichtigen, vor allem in der gegenwärtigen Situation, da sie monetarisiert werden müssen. Schadensfunktionen behandeln daher katastrophale Schäden entweder gar nicht, unvollständig oder willkürlich. Manchmal werden sie mit einem Ad-hoc-Zuschlag berücksichtigt. Teile der Literatur fordern, dass die Wahrscheinlichkeit einer Katastrophe im Sinne eines Versicherungsansatzes der wesentliche Treiber für die Klimaschutzpolitik sein sollte. Dann sollte Klimawandel bestimmte Schwellen nicht überschritten, um die Möglichkeit katastrophaler Schäden zu minimiert.
- Der Klimawandel bringt eine Vielzahl von **nicht marktwirtschaftlichen Auswirkungen** mit sich, die entweder nicht direkt mit dem menschlichen Wohlergehen zusammenhängen (z.B. Verlust der Biodiversität) oder für die es keine direkte Marktbewertung gibt (d.h. erhöhte Sterblichkeit). Um ein vollständiges Bild zu vermitteln, ist es wichtig, diese Auswirkungen zu berücksichtigen. Dies ist jedoch schwierig, da nicht marktwirtschaftliche Auswirkungen monetarisiert und in die ökonomische Metrik der Schadensmodelle (e.g. BIP oder Gesamtverbrauch) übersetzt werden müssen. Die entsprechenden Methoden sind umstritten und mit großen Unsicherheiten behaftet ist (z.B. Zahlungsbereitschaft, um bestimmte Auswirkungen zu verhindern, oder der statistische Wert eines Lebens).
- Schließlich sollten die Modelle die begrenzte Substituierbarkeit zwischen Natur- und Marktgütern berücksichtigen (z.B. durch **ökologische Diskontierung**). Es gibt verschiedene Möglichkeiten, die Schadensfunktion entsprechend zu erweitern, aber die Datenlage ist dürftig und die Methoden unterscheiden sich erheblich.

Schadensmodelle — auf das Wesentliche reduziert — modellieren, dass Treibhausgasemissionen das Klima ändern, monetarisieren die daraus resultierenden biophysikalischen Auswirkungen und aggregieren diese Werte über Raum und Zeit. Jeder dieser Schritte ist mit Unsicherheit verbunden, und es gibt viele Freiheitsgrade hinsichtlich des Modellierungsansatzes. Folglich verfügen die Entwickler von Schadensmodellen bei der Bestimmung des SCC über einen erheblichen Ermessensspielraum. Durch die Vorgabe von Anforderungen an Szenarien und (normative) Wahlmöglichkeiten sowie die Forderung nach obligatorischen Erweiterungen der Schadensfunktion kann dieser Ermessensspielraum von den Anwendern teilweise eingeschränkt werden.

Ein alternativer Weg zur Ableitung von SCC sind Expertenerhebungen (diese Studien fragen entweder direkt nach den SCC oder leiten sie aus den Antworten ab). Die Ergebnisse sind ebenso unsicher wie die von Modellen, da Experten kaum Möglichkeiten haben, robustere Antworten als Modelle zu geben. Zudem werden viele Expertenurteile wiederum auf Modellen basieren.

Vermeidungskosten: Einflussfaktoren und Annahmen

Vermeidungskostenmodelle monetarisieren die Kosten der Emissionsreduzierung. In der Literatur werden **verschiedene Konzepte zur Messung von Vermeidungskosten** verwendet. Viele Vermeidungskostenmodelle geben den CO2-Preis (oder Emissionspreis) an, der sich z.B. aus der Auferlegung eines vordefinierten Minderungsziels (z.B. eines CO2-Budgets) ergibt. Unter idealisierten Bedingungen spiegelt der Emissionspreis die **Grenz-Vermeidungskosten** (MAC) wider, d.h. die Kosten einer inkrementellen Emissionsreduktion um eine Einheit.[2] Da die Emissionspreise jedoch nur die Kosten der Minderung der letzten und damit teuersten Emissionseinheit widerspiegeln, erlauben sie keine Aussagen über die **Gesamt- oder Durchschnittskosten der Klimaschutzpolitik**. Um letztere zu messen, verwenden die Modelle wiederum unterschiedliche Kostenmetriken (die Fläche unter der MAC-Kurve, die Veränderung des (aggregierten) Konsums, die Veränderung des Bruttoinlandsprodukts (BIP), die zusätzlichen Gesamtenergiesystemkosten oder die (zusätzlichen) Investitionskosten im Vergleich zu einem Basisszenario).

Auf der methodischen Seite gibt es eine Vielzahl unterschiedlicher Modelle und zugrunde liegender Ansätze zur Bewertung langfristiger Transformationspfade und der daraus resultierenden Kosten für gegebene Minderungsziele (Cost-Effectiveness-Perspektive). Im Allgemeinen geht ein **höherer Detaillierungs- und Komplexitätsgrad auf Kosten einer notwendigen Vereinfachung in anderen Bereichen**. Im Großen und Ganzen lassen sich zwei Hauptperspektiven unterscheiden. Die Stärke einer Bottom-up-Perspektive liegt in der Art und Weise, wie sie "heranzoomt" und ein hohes Maß an technischen Details präsentiert. Im Gegensatz dazu zielt eine Top-Down-Perspektive darauf ab, "herauszuzoomen", indem sie das "große Ganze" einschließlich gesamtwirtschaftlicher Aspekte darstellt. Komplexe Vermeidungskostenmodelle bestehen typischerweise aus einer Kombination verschiedener Modellkomponenten und können beide Perspektiven kombinieren (Hybridmodelle).

Eine weitere Dimension der Modellkomplexität ist die **regionale Abdeckung**. Im Hinblick auf Metastudien, die langfristige Minderungspfade und die damit verbundenen Vermeidungskosten analysieren (z.B. die Sachstandsberichte des Weltklimarats IPCC), stehen **globale Modelle** im Vordergrund. Die grobe zeitliche und räumliche Disaggregation globaler Modelle wird oft kritisiert, weil sie die Komplexität der realen Welt und die sozio-politischen Dimensionen nur begrenzt abbilden können und für die Politikgestaltung auf nationaler Ebene nur von begrenztem Nutzen sind. Daher gibt es auch eine große Bandbreite an länder- und regionsspezifischen Modellen. **EU-fokussierte oder auf Deutschland fokussierte Modelle** ermöglichen eine detailliertere Darstellung von Ländermerkmalen und Heterogenität. Sie sind jedoch weniger geeignet, das "große Ganze" zu vermitteln und globale Implikationen und Dekarbonisierungszusammenhänge zwischen Regionen zu bewerten, wie dies in globalen Modellen geschieht. Darüber hinaus gibt es nur wenige systematische (Meta-)Analysen der Einflussfaktoren für Vermeidungskosten auf regionaler Ebene, während in vielen globalen Modellen regelmäßig Modellvergleichsstudien durchgeführt werden.

Da das Pariser Abkommen als politischer Richtwert dient, kann die Vielzahl der vorhandenen Schätzungen der Vermeidungskosten durch die Fokussierung auf Szenarien, die im Einklang mit

[2] Es ist zu beachten, dass der Emissionspreis nur unter idealisierten und vereinfachten Annahmen den Grenzvermeidungskosten entspricht. Wenn z.B. bereits eine andere Umweltpolitik umgesetzt wird, unterschätzt der Emissionspreis die wahren Grenzvermeidungskosten, da ein Teil der Emissionsreduktionen durch die andere Politik erreicht wird.

dem Pariser Abkommen stehen, eingegrenzt werden. Trotzdem bleibt die Bandbreite der Schätzungen der Vermeidungskosten aufgrund der Unterschiede in den zugrunde liegenden Annahmen groß. Bei diesen Annahmen kann es sich um modellspezifische Merkmale oder um Parameter handeln, die für verschiedene Modellläufe, die unterschiedliche Szenarien widerspiegeln, variiert werden können. Bei letzteren ist es möglich diese (zumindest bis zu einem gewissen Grad) modellübergreifend für Vergleiche zwischen Modellen zu harmonisieren. Alle diese Elemente weisen sowohl normative Komponenten als auch wissenschaftliche Unsicherheit und technische Limitationen auf. Modellspezifische Faktoren lassen sich weiter differenzieren in strukturelle Elemente und Elemente, die wir 'Ausschluss-/Einschlussentscheidungen' nennen.

Die wesentlichsten **Szenarioannahmen** sind:

- **Sozioökonomische Narrative** (z.B. die "Shared Socio-economic Pathways" (SSPs)) sind Story-Lines, die Annahmen über (potentielle) sozioökonomische Entwicklungen (u.a. wirtschaftliche Entwicklung, Bevölkerung, Lebensstil, Hürden der Technologieverbreitung, regionale Rivalität) umreißen und somit das Ausmaß der Herausforderungen für die Emissionsvermeidung widerspiegeln. Es überrascht nicht, dass SSPs mit höheren Herausforderungen für die Emissionsminderung mit höheren Vermeidungskosten in Zusammenhang stehen oder sogar dazu führen, dass manche Modelle keine Lösung für ehrgeiziger Emissionsminderungsziele errechnen können.

- Grundlegende Annahmen definieren kontrafaktische zukünftige Entwicklungen in Abwesenheit einer (zusätzlichen) Klimapolitik (**Baseline**) und stehen in engem Zusammenhang mit den oben genannten sozioökonomischen Narrativen.

- Um die inhärenten politökonomischen Unsicherheiten zukünftiger Szenarien widerzuspiegeln und um die in globalen Modellen übliche Annahme eines weltweit einheitlichen Emissionspreises mit quasi sofortiger Umsetzung in Frage zu stellen, haben Studien die Auswirkungen mehrerer alternativer **Politik-Annahmen** bewertet. Fragmentiertes Handeln (d.h. keine globale Zusammenarbeit) erhöht in der Regel die Kosten der Emissionsminderung. Ebenso wenn angenommen wird, dass Emissionen aus bestimmten Sektoren, wie z.B. der Landnutzung, aus praktischen Gründen nicht vom Emissionspreis abgedeckt werden können, müssen höhere Emissionspreise in anderen Sektoren dies ausgleichen. Auch eine Verzögerung des Klimaschutzes führt sowohl in globalen als auch in regionalen (EU)-Modellen zu einem erheblichen Anstieg der Vermeidungskosten, was teilweise zu prohibitiv hohen Emissionspreisen führt bis hin zu Schwierigkeiten einiger Modelle, Ergebnisse produzieren zu können.

Die Umsetzung von Annahmen, die je nach Pfad variieren, hängt auch mit verschiedenen **normativen Entscheidungen** zusammen. Die relevantesten sind:

- Die **Emissions- oder Temperaturgrenze** ist eine wichtige normative Wahl, wobei das Pariser Abkommen seit 2015 einen klaren Maßstab darstellt. Zusammen mit dem in Artikel 4 formulierten Ziel einer Treibhausgasminderung hin zur Netto-Null definiert Artikel 2.1 eine langfristige Temperaturgrenze von deutlich unter 2°C über dem vorindustriellen Niveau und die Fortsetzung der Bemühungen, den Temperaturanstieg auf 1,5°C über dem vorindustriellen Niveau zu begrenzen. Diese Formulierung lässt jedoch

Interpretationsspielraum darüber, ob und in welchem Maße Artikel 2.1 eine **begrenzte Überschreitu**ng (‚Overshoot') der langfristigen Temperaturgrenze von 1,5°C zulässt. Daraus ergeben sich zwei wichtige zusätzliche normative Wahlmöglichkeiten. Erstens, ob und wenn ja, um wie viel eine vorübergehende Überschreitung des Ziels erlaubt ist, solange der Grenzwert z.B. bis zum Ende des Jahrhunderts eingehalten wird. Abhängig von der erlaubten Überschreitung können sich zwei mit "1,5°C" bezeichnete Szenarien auf sehr unterschiedliche mittlere globale Spitzentemperaturänderungen und damit verbundene Klimaschäden beziehen. Zweitens ist die Wahl einer höheren **Wahrscheinlichkeit unter der festgelegten Temperaturgrenze zu bleiben**, mit einem ehrgeizigeren Ziel und geringeren zu erwartenden Schäden verbunden. Die Wahrscheinlichkeit spiegelt die verbleibenden wissenschaftlichen Unsicherheiten in Bezug auf das Klimasystem und die Übersetzung der Emissionswerte in Temperaturänderungen wider. Szenarien, die hohe Überschreitungen in Kombination mit hohen Diskontsätzen zulassen, verlagern typischerweise die Minderungslast in die Zukunft und führen zu niedrigeren Emissionspreisen in der kurzen Frist auf Kosten stark steigender Emissionspreise in der längeren Frist (insbesondere in intertemporalen Optimierungsmodellen).

- **Regionale Verteilung der Kosten und „Burden sharing"-Ansätze**: Globale Modelle gehen häufig davon aus, dass Klimaschutz dort betrieben wird, wo er global am billigsten ist, wobei politische Realitäten und Aspekte wie die historische Verantwortung oder die Frage, wer für den Klimaschutz bezahlt, außer Acht gelassen werden. Um dem Rechnung zu tragen, können globale Modelle verschiedene Lastenverteilungsschemata (‚Burden Sharing) auferlegen, um die Minderungsbemühungen auf Regionen oder Länder zu verteilen, wobei wenig Einigkeit darüber besteht, welches Schema als "fair" angesehen werden kann. In Wirklichkeit ist es unwahrscheinlich, dass die Verteilung der Minderungsaktivitäten zwischen den Regionen diesen gewählten idealisierten Rahmenbedingungen folgt, was wahrscheinlich zu höheren Minderungskosten führt. Darüber hinaus "frieren" viele globale Modelle die derzeitigen globalen ungleichen Einkommensmuster ein, um modellbedingte hohe Finanztransfers und Einkommensumverteilung in den Modellergebnissen zu vermeiden.

- **Diskontierung (Wahl des Schemas und der Parameter):** Während in Vermeidungsmodellen der Diskontierungssatz die (vordefinierte) Wahl des Vermeidungsziels an sich nicht beeinflusst, hat er doch direkte Auswirkungen auf i) den Transformationspfad im Zeitablauf, ii) den Technologiemix und iii) die Höhe des Overshoot und damit der damit verbundenen Schäden. Die Diskontierung hat starke Auswirkungen auf die intergenerationelle Gerechtigkeit, da höhere Diskontierungssätze die Minderungsbemühungen und -kosten in die Zukunft verlagern. Dies ist z.B. besonders relevant für den großflächigen Einsatz von (kostspieligen) Technologien wie z.B. Technologien für negative Emissionen. In der aktuellen Literatur sind Diskontierungssätze in Modellen für Vermeidungskosten von etwa 5% üblich, wobei es jedoch häufig an Transparenz mangelt. Im Gegensatz zur Literatur über die Schadenskosten (‚Social Costs of Carbon') wird die Rolle der Wahl des Diskontsatzes in Vermeidungskostenmodellen nur selten diskutiert, und Sensitivitätsanalysen hierzu sind kaum verfügbar.

- Modellierer haben in der Regel einen großen Ermessensspielraum bei der Umsetzung von techno-ökonomischen Annahmen in Form von **Modellvorgaben bei Technologieoptionen und -parametern**, zum Beispiel bei der Umsetzung sozio-ökonomischer Narrative:
  - Diese Modellvorgaben können damit zusammenhängen, dass der **Einsatz bestimmter Technologien im Modell eingeschränkt** wird, um eine geringe öffentliche Akzeptanz (z.B. Atomkraft oder Kohlenstoffabscheidung und -speicherung (CCS)) oder Nachhaltigkeitsbedenken (z.B. Bioenergie mit CCS) widerzuspiegeln. Der Ausschluss von kostenkompatiblen Technologieoptionen erhöht in der Regel die Vermeidungskosten. Der Ausschluss oder die Einschränkung von Technologien mit negativen Emissionen (NETs) hat Auswirkungen auf die intertemporale Verteilung von Anstrengungen und Kosten, da weniger effektive kurzfristige Anstrengungen nicht durch negative Emissionen in der zweiten Hälfte des Jahrhunderts kompensiert werden können, wodurch die kurzfristigen Minderungskosten steigen. Darüber hinaus sind mehrere kürzliche Entwicklungen bei neuen Technologien, wie Wasserstoff oder Direct Air Capture, in vielen (globalen) Minderungsmodellen noch immer unterrepräsentiert.
  - Auferlegte Modellbeschränkungen können auch die **Geschwindigkeit des Ausstiegs aus konventionellen (kohlenstoffintensiven) Technologien oder des Ausbaus neuer (kohlenstoffarmer) Technologien einschränken**. Im Vergleich zu den beobachteten Entwicklungen in der Realität haben globale Minderungsmodelle in der Regel die künftigen Technologiekosten von Erneuerbaren (wie Wind- und Solarenergie) überschätzt und ihre tatsächlichen Wachstumsraten unterschätzt. Dies hat Auswirkungen auf den sich daraus ergebenden Technologiemix, aus dem teilweise Politikempfehlungen abgeleitet werden. Wenn man davon ausgeht, dass die Geschwindigkeit des Ausstiegs aus fossilen Technologien gering sein muss, werden mehr CCS- und Technologien mit negativen Emissionen benötigt, um einen langsameren Übergang auszugleichen. Optimistischere Annahmen über die Verbreitung von Technologien für erneuerbare Energien senken in der Regel die Vermeidungskosten, insbesondere in Kombination mit endogenem technologischen Wandel.

Strukturelle Elemente charakterisieren die inhärente Wahl des Modellaufbaus. Wichtige strukturelle Elemente von Vermeidungskostenmodellen sind:

- **Darstellung der Makro-Ökonomie und des Gleichgewicht-Typs:** Zu den häufig verwendeten Modellen gehören i) Bottom-up-Modelle unter Verwendung eines partiellen Gleichgewichts (häufig Energiesystem-Modelle), ii) (Optimal-Growth) Wachstumsmodelle unter Annahme eines allgemeinen Gleichgewichts (General Equilibrium) und einer vereinfachten Darstellung der Makro-Ökonomie und iii) Computable General Equilibrium Modelle (CGE) mit einer detaillierten Darstellung der sektoralen Verflechtungen. Alle diese Modelltypen gehen von der Annahme eines Gleichgewichts- und Optimierungsprozesses aus. Es ist jedoch zu beachten, dass die Ausgangsannahme, dass sich die Wirtschaft vor der Einführung der Klimapolitik im Gleichgewicht und damit im Optimum befindet, zwangsläufig (per Definition) makroökonomische Kosten verursacht, die sich aus der Klimapolitik ergeben (durch Abweichung vom Gleichgewicht). Dies spiegelt eine bestimmte Weltsicht wider, die durch Modelle in Frage gestellt wird, die bereits bestehende Ineffizienzen annehmen (z.B. bisher weniger häufig verwendete ("Non-Equilibrium"-Modelle). In diesen kann Klimapolitik sogar zu wirtschaftlichen Vorteilen führen. Die Vermeidungskosten sind in Allgemeinen Gleichgewichtsmodellen tendenziell höher als in Partialgleichgewichtsmodellen, da letztere typischerweise Rückkopplungseffekte und Umsetzungsbarrieren für die Gesamtwirtschaft außer Acht lassen. Höhere Kosten in CGE-Modellen im Vergleich zu Optimal Growth-Modellen hängen damit zusammen, dass CGE-Modelle die Interaktionen zwischen den Sektoren und die gesamtwirtschaftliche Verzerrung besser abbilden, sowie mit den Unterschieden im Vorausschau-Mechanismus, der typischerweise in diesen jeweiligen Modelltypen angewandt wird.

- **Perfekte Voraussicht vs. myopische Erwartungen:** Die beiden Haupttypen zur Berücksichtigung zukünftiger Informationen: i) myopische Erwartungen, die typischerweise von CGE-Modellen angewendet werden, oder ii) perfekte Voraussicht, ein vorausschauender Ansatz, der über den gesamten Zeithorizont optimiert und typischerweise von Optimal Growth-Modellen angewendet wird. Der myopische Ansatz geht davon aus, dass eher "kurzsichtige" Akteure Investitionsentscheidungen auf der Grundlage der in der jeweiligen Periode verfügbaren Informationen treffen, ohne die Zukunft zu kennen. Perfect-Foresight-Modelle gehen dagegen von einer langfristigen, vorausschauenden Planungsperspektive hin zum intertemporalen Optimum aus, wobei perfekte Informationen über zukünftige Kosten angenommen werden. Modelle der perfekten Voraussicht (Optimal-Growth Modelle) tendieren dazu, im Vergleich zu myopischen (CGE) Modellen - zumindest auf kurze Sicht - niedrigere Emissionspreise zu erzielen. Dies liegt daran, dass die Annahme einer perfekten Voraussicht eine effizientere Verteilung der Emissionsreduktionen im Laufe der Zeit ermöglicht. Darüber hinaus abstrahieren Modelle des optimalen Wachstums typischerweise Verzerrungen oder Interaktionseffekte zwischen Sektoren, die ein Merkmal von CGE-Modellen sind. Modelle mit perfekter Voraussicht (Optimal-Growth Modelle) weisen jedoch typischerweise exponentiell steigende Emissionspreise im Laufe der Zeit auf, was zu vergleichsweise höheren langfristigen Emissionspreisen führt.

- **Technologischer Fortschritt:** Im Großen und Ganzen lassen sich Modelle in solche einteilen, bei denen technologischer Fortschritt exogen angenommen ist, und solche, die technologischen Fortschritt endogen modellieren (z.B. durch "learning by doing"). Modelle, die von perfekter Voraussicht, ergänzt durch endogenen technologischen Fortschritt, ausgehen, finden tendenziell niedrigere aggregierte Vermeidungskosten. Die Annahme des endogenen technologischen Fortschritts führt dazu, Anreize für frühere Investitionen in kohlenstoffarme Technologien zu schaffen, wodurch die Vermeidungskosten in der kurzen Frist steigen, die Kosten in der langen Frist jedoch sinken.

- **Abdeckung von unterschiedlichen Treibhausgasen (GHGs):** Während CO2 für den Energiesektor dominiert, spielen Nicht-CO2-Treibhausgase eine wichtige Rolle in anderen Sektoren wie Landwirtschaft, Abwasseraufbereitung oder industriellen Prozessen. Ein Multi-Gas-Ansatz ermöglicht mehr Flexibilität bei der Minderung und damit zumindest kurzfristig eine Kostenreduktion, da einige Nicht-CO2-Minderungsoptionen vergleichsweise kostengünstig sind (z.B. die Beseitigung von Lachgas in industriellen Prozessen). In anderen Sektoren ist die Minderung von Nicht-CO2-Gasen jedoch schwieriger (z.B. Methanemissionen aus der Viehzucht oder Distickstoffoxidemissionen aus der Düngemittelverwendung), was eine große Herausforderung für das Erreichen von Null-Emissionen auf lange Sicht darstellt.

Elemente, die wir als **"Ausschluss-/Einschlussentscheidungen"** betrachten würden, sind Elemente eines Modells, die in verschiedenen Modellversionen ein- oder ausgeschlossen werden können, aber dennoch eine Art strukturelles Modul darstellen, das das Modell charakterisiert:

- Verschiedene Arten positiver (oder negativer) Nebeneffekte von Minderungsmaßnahmen können innerhalb der Modelle bei der Bewertung der Vermeidungskosten berücksichtigt werden, wie z.B. Zielkonflikte bei der Ernährungssicherheit oder gesundheitliche Vorteile durch geringere Luftverschmutzung. Dies erfordert die Monetarisierung solcher (oft nicht-monetärer) Nebeneffekte, welchen Werturteile mit sich bringt. Mehrere Studien, die z.B. den gesundheitlichen Zusatznutzen berücksichtigen, kommen zu dem Ergebnis, dass dieser die Vermeidungskosten in bestimmten Regionen teilweise oder sogar vollständig aufwiegen könnte.
- Darstellung von Vermeidungsoptionen: Einige Modelle berücksichtigen die Ausgestaltung von Politikinstrumenten wie Effizienzstandards oder Subventionen für bestimmte (kohlenstoffarme) Technologien. Die Analyse solcher Maßnahmen spielt typischerweise eine wichtige Rolle in regionalen oder nationalen Modellen, in denen ein Emissionspreis oft nicht die Hauptantriebskraft für Emissionsreduktionen ist. Darüber hinaus heben in globalen Studien Szenarien mit geringer Energienachfrage die Rolle der sogenannten nachfrageseitigen Minderungsoptionen hervor. Sie zeigen, dass Änderungen der Konsumverhaltensweisen hin zu nachhaltigeren Lebensstilen (z.B. reduzierter Stromverbrauch, Ernährungsumstellungen) die Minderungskosten erheblich senken und auch den Bedarf an Technologien mit negativen Emissionen reduzieren können.
- Modelle können sich auch dazu entscheiden, "reale" Unvollkommenheiten wie Marktbarrieren darstellen, entweder als Teil des strukturellen Aufbaus oder z.B. in Form von Kostenaufschlägen. Bereits bestehende Ineffizienzen ermöglichen Potential für negative Kosten, aber Marktbarrieren können auch die Minderungskosten erhöhen.

Relevanz von Modellen zu Klimakosten für die Klimapolitik

Sowohl Modelle zu den Vermeidungskosten als auch zu den Schadenskosten sind komplex. Sie enthalten Annahmen über zahlreiche Einflussfaktoren, so dass die Ergebnisse mit Unsicherheit behaftet sind. Daher erfordert eine korrekte Interpretation der Ergebnisse ein fundiertes Verständnis dieser Annahmen und Einflussfaktoren. Ergebnisse sollten niemals als "bare Münze" oder als genaue Vorhersagen künftiger Ereignisse betrachtet werden. Dies gilt zwar generell für Modelle jeglicher Art, ist aber im Zusammenhang mit der Modellierung von Klimakosten besonders relevant. Der langfristige Zeithorizont des Klimawandels, die Trägheit der beteiligten Systeme sowie das komplexe Zusammenspiel von sozioökonomischen, verhaltensbezogenen und physikalischen Aspekten des Klimawandels führen zu grossen Unsicherheiten.

Viele Wissenschaftler argumentieren daher, dass der Hauptbeitrag von Vermeidungskosten- und Schadenskostenmodellen nicht darin besteht, exakte Zahlen zu liefern, sondern Einsichten: Sie sind ein kohärenter und konsistenter Weg, komplexe Sachverhalte zu hinterfragen und Annahmen und Ansätze transparent zu machen. Sie sind zudem ein Instrument des Risikomanagements für künftige Klimaschäden und Vermeidungskosten.

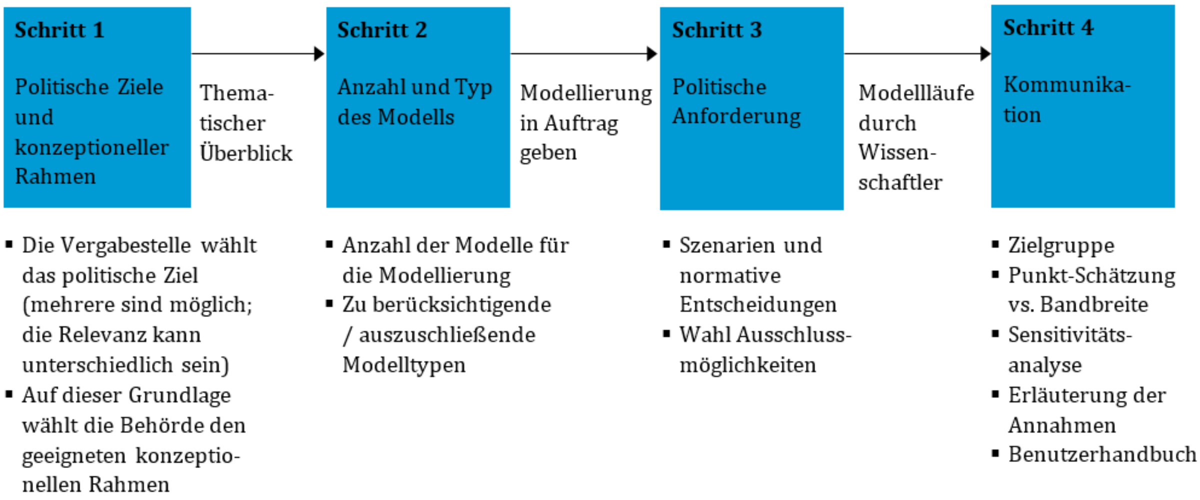
Dennoch ist ein Preisschild für Treibhausgasemissionen ein entscheidender Bestandteil jeder Klimapolitik. In den aktuellen öffentlichen Debatten sind die Kosten und wirtschaftlichen Auswirkungen politischer Entscheidungen ein zentrales Element, um die Relevanz eines politischen Themas einzuschätzen. Auch wenn die Ungewissheit groß ist, ist es für politische Entscheidungen von entscheidender Bedeutung, die wissenschaftsbasierte Größenordnung der Kosten zu kennen. Ein Preisschild ist somit nötig, auch wenn es keinen wissenschaftlichen Konsens über den angemessenen Wert gibt. Es ist jedoch wichtig, die Unsicherheit, die mit Modellschätzungen einhergehen, angemessen zu kommunizieren und eine strukturierte Diskussion über die wichtigsten Einflussfaktoren zu ermöglichen.

Aus einer breiteren Perspektive betrachtet, ist ein Preisschild nur eines von vielen Elementen, die eine umfassende Klimapolitik erfordert. In diesem breiteren Kontext spielen Vermeidungskostenmodelle eine weitere Rolle: Ihr primäres Ziel besteht häufig darin, wirtschaftlich oder technisch optimale Transformationspfade zu identifizieren und zu analysieren. Die daraus resultierenden Vermeidungskosten sind hingegen eine sekundäre Information. Dies gilt insbesondere für nationale Modelle, die politische Handlungsfelder identifizieren, zusätzlichen Investitionsbedarf beschreiben. Zudem erlauben sie es, eine konsistente und kosteneffiziente Strategie zur Emissionsreduktion zu entwerfen.

Eine Anleitung in vier Schritten zur Ableitung von Klimakostenschätzungen

Wir schlagen einen vierstufigen Prozess zur Ableitung von Klimakosten vor, wie in der folgenden Abbildung dargestellt. Wir konzentrieren uns auf den *Prozess,* empfehlen aber keine spezifischen Werte oder Bereiche für die jeweiligen Parameter oder Resultate.

Abbildung B: Die 4 Schritte für eine Vergabestelle zur Bereitstellung von Informationen über Klimakosten



Quelle: eigene Darstellung, Infras

In Schritt 1 definiert die Vergabestelle den konzeptionellen Rahmen auf der Grundlage ihrer politischen Ziele. In Schritt 2 wählt die Vergabestelle Modelle aus, um Klimakostenschätzungen abzuleiten. Diese Wahl betrifft sowohl die Anzahl der Modelle als auch den/die Modelltyp(en). Die Vergabestelle kann auch Modelle zur Durchführung spezifischer Analysen in Auftrag geben. In Schritt 3 schreibt die Vergabestelle politische Anforderungen für bestimmte Kategorien von Einflussfaktoren vor. Diese Anforderungen werden die Unsicherheitsspanne der Literatur bis zu einem gewissen Grad verringern. Die verbleibende Bandbreite ergibt sich in erster Linie aus der wissenschaftlichen Unsicherheit und den Szenarien. In Schritt 4 schließlich verwendet der Auftraggeber die Modellergebnisse, um Schätzungen der Klimakosten zu kommunizieren. Dabei muss immer ein Kompromiss zwischen Einfachheit und wissenschaftlicher Vollständigkeit eingegangen werden. Die Nutzer sind in erster Linie an einfach zu verwendenden Zahlen interessiert. Gleichzeitig sollten die Vorbehalte bezüglich der Modelle, wie oben diskutiert, dem Benutzer in geeigneter Weise vermittelt werden.

Part 1 Introduction

This study is structured as follows. Part 1 presents the background and aim of the study and introduces the notions of damage costs and mitigation costs as the conceptual frameworks to derive climate costs. It also provides general information on models as the main tool to derive those costs, discusses the various typologies of uncertainties and scenarios used and shows existing policy application of climate costs. Parts 2 and 3 describe and analyse in detail influencing factors for the damage costs and the mitigation costs framework, respectively. These parts are each concluded by a findings chapter. Finally, Part 4 synthesizes the overall findings of parts 1–3. It contains a comparison of the frameworks and guidance in four steps for a contracting authority to provide climate cost estimates.

1 Background and aim of the study

Climate change is one of the greatest challenges mankind currently faces. It will lead to significant damages even if constrained to a global mean temperature increase of 1.5°C above pre-industrial levels. Without such stringent mitigation efforts, damages will be even higher. Assessing the scale of the damages is important to strengthen political as well as public support for ambitious climate action. The current Method Convention 3.0 of the German Environment Agency thus recommends for greenhouse gas emissions in the year 2016 a cost rate of 180 $€_{2016}/tCO_{2eq}$ and a sensitivity analysis of 640 $€_{2016}/tCO_{2eq}$.These number are based on the model FUND, which calculates and aggregates damages for current and future generations. These results are strongly dependent on assumptions with respect to various influencing factors. For example, the discrepancy of UBA's numbers solely arise for assuming a pure rate of time preference (which is a crucial part of the discount rate) of 1% or 0%, respectively. For this and other influencing factors, there is an ongoing debate on a scientific, economic, social, and political level about the appropriate choice. Consequently, the estimates of climate damages in the scientific literature differ considerably.

Focusing on damages, the German Environment Agency uses the damage costs framework to derive "climate costs". Mitigation costs are the other framework to calculate climate costs in case the focus is on the costs to reduce greenhouse gas emissions (usually in accordance to the Paris Agreement where countries in article 2 agreed to limit global mean temperature increase to "well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C"). Mitigation costs estimations are equally uncertain, as assumptions on influencing factors differ widely. Some challenges are the same as for damage costs (e.g. the discount rate), others are new (e.g. technological progress).

Against this background, this study has the following main objectives:

- Provide a comprehensive overview of the literature on climate costs
- Analyse the significance and impact of different influencing factors and assumptions for estimates of damage costs and mitigation costs.
- Separate assumptions into different types.
- Recommend a procedure to quantify the climate costs for future Method Conventions of the German Environment Agency.

2 Setting

2.1 Conceptual frameworks to derive climate costs

Damages costs and mitigation costs are two frameworks to derive climate costs. The following table explains the basic conceptual differences and the areas of applicability.

Table 1: Frameworks to derive climate costs

	Damage Costs	Mitigation Costs
Explanation	• Relate to the various damages caused by the emissions of greenhouses gases • Includes adaptation costs[3] • Often expressed in terms of social costs of carbon (SCC)[4] which is the • SCC are defined marginally, but damage costs may also be calculated as total costs or average costs[5] • SCC usually increase if baseline emissions are higher • Covered in Part 2 of this report	• Accrue due to the implementation of measures to reduce emissions • May include co-benefits (e.g. clean air) • Several calculation approaches: economy-wide marginal, average or total costs compared to a baseline scenario[6] • Refers to specific measures, specific sectors, or the whole economy • Increase with more ambitious mitigation efforts • Covered in Part 3 or this report
Applicability (Examples)	• Internalisation of external costs ("polluter pays"-principle) • Benefits in terms of avoided damages when conducting a cost-benefit analysis of a policy or specific mitigation investment	• Appropriate tax rate to achieve a predefined mitigation target (overall or for a specific sector) • Costs of a certain mitigation policy

Source: own illustration, Infras

Figure 1 highlights that mitigation and damage costs are functions of emission in diametrically opposite directions: higher CO_2-emissions imply lower mitigation costs but entail higher damage costs and vice versa.

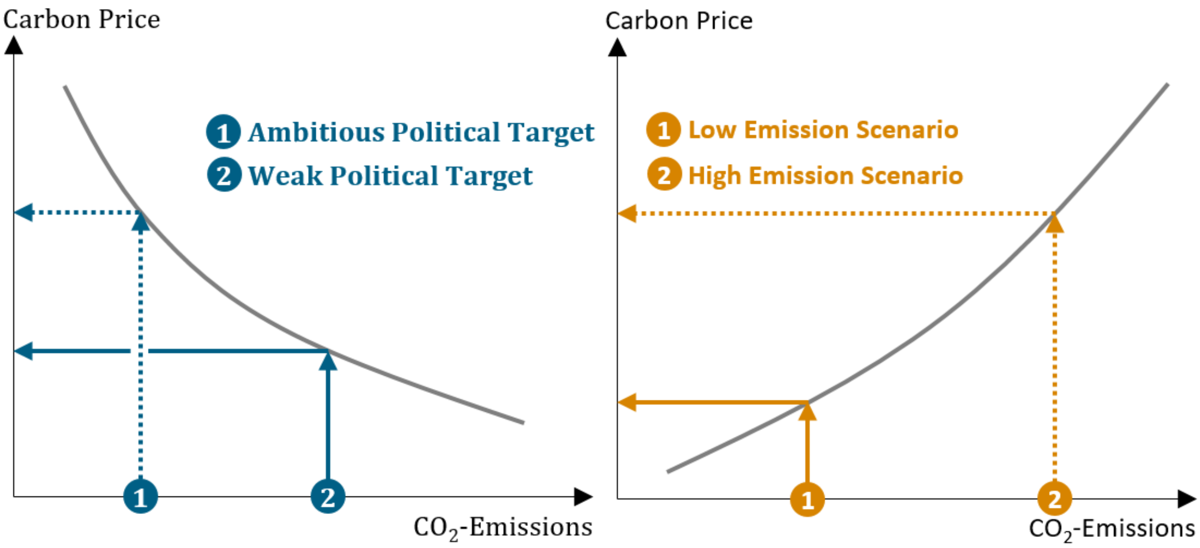
[3] Adaptation reduces damages but usually entails additional investments.

[4] Discounted sum of future climate damages caused by emitting one additional ton of CO_2.

[5] There are further possible metrics, such as percentage loss of GDP per year, total economic cost per year, net present value of damages, average damage costs per year, or reduction of the balanced growth path (as in Stern 2006).

[6] Average or total costs are typically based on percentage loss of GDP or consumption, or additional total energy system costs compared to the baseline.

Figure 1: Climate Costs and CO_2-Emission



The shapes of the curves are purely illustrative. Furthermore, the illustration simplifies various aspects (e.g. the time-dependence of carbon prices) and neglects other influencing factors.
Source: own illustration, Infras

As explained in Box 1, a further difference between the two frameworks are the applied cost concepts.

Box 1: Cost concepts of damages and mitigation

For *damage* costs, there exists a large and dedicated body of literature concerned with the social costs of carbon (SCC). SCC is a metric explicitly defined to represent the external costs of emissions. There is thus a broad agreement that the SCC are a suitable metric to quantify damage costs associated with an emission unit. For other purposes, there are further damage metrics discussed in the literature, such as total damages, current GDP losses or balanced growth equivalents (Stern, 2007).

Mitigation costs are presented either as total costs, as average costs, or as marginal costs. Marginal costs are typically modelled as the price an emitter must pay per tonne of carbon such that a given carbon budget constraint is fulfilled (so called shadow price). Total or average costs may be based on different metrics, such as change in GDP or consumption or additional energy system costs compared to the baseline scenario. Whether average or marginal costs are more suitable depends on the context. To determine a tax level, for example, marginal costs are usually considered more appropriate. To provide information on the costs of mitigation, average costs may be more helpful. Finally, note that average mitigation costs may be defined either as the average costs over a certain year or over a longer time horizon

There is a third modelling framework: One may consider damage *and* mitigation costs in parallel. This framework is not the focus of this study (see Box 2). We thus only briefly discuss cost-benefit integrated assessment models (CB-IAM) that use it as a special case of damage cost models in Section 10.

Box 2: Why the cost-benefit framework is not a focus of this study

The cost-benefit framework compares the costs of climate action to the costs of inaction. More precisely, cost-benefit integrated assessment models (CB-IAM) quantify mitigation costs and damage costs (avoided damages are the "benefit") in parallel and subsequently determine the emission trajectory (and the corresponding carbon prices) for which the sum of these two costs is minimal.

Constructing a CB-IAM is however very challenging, as mitigation and damages have, among other differences, different time horizons, cost concepts or sectors of relevance. In addition, CB-IAM are conceptually questionable, as they assume (1) that all damages and mitigation costs can be monetized and hence compared and (2) that lower mitigation costs in the present generation can compensate for higher climate damages in later generations (or vice versa).

Most importantly though, a CB-IAM's major selling point is their ability to provide an "optimal" emission trajectory and an "optimal" temperature increase. Yet, with the commitment to the Paris Agreement this exercise has become de-facto obsolete: The Paris Agreement represents the international political consensus to limit the global mean temperature increase to "well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels" (Paris Agreement[7], Article 2). This temperature limits represents a political choice and is more comprehensive than any model estimate could be.[8] Given this consensus on the one side and the high modelling uncertainty on the other side, a CB-IAM exercise that yields a "optimal" temperature increase higher the Paris Agreement's limits is of little policy relevance.

2.2 Models as the main tool to calculate climate costs

2.2.1 Overview

Models play an important role in providing information on the main parameters that influence climate costs and thus assist policy formation. Their set-up and the underlying explicit and implicit assumptions are the focus of this study. Consistent with the frameworks defined above, we distinguish two major model-types:

Damages models calculate the SCC based on a damage function which translates physical climate impacts into monetary damages. Damage models need as input a specific emission scenario that determines the level of climate change assumed in the model calculations. Damage models are closely connected to CB-IAM, because they are usually the same models with the mitigation component "switched off".[9]

Mitigation models determine the mitigation costs for a given pair of baseline and target emissions (or temperature limits that correspond to these emission levels). More specifically, they calculate the most cost-effective way (e.g. with respect to the technology mix) of achieving a target or limit. They include a higher-order description of the economy including several sectors, the energy system and — usually — land-use change.[10] Some mitigation cost models can also be

[7] https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement (27.11.2020)

[8] On the origin of the 2°C target see https://www.carbonbrief.org/two-degrees-the-history-of-climate-changes-speed-limit (27.11.2020).

[9] A damage model is thus in a sense a CB-IAM which evaluates the damage costs for — in the logic of the model — non-optimal emissions. Emission trajectories are in this case an exogenous input.

[10] A mitigation cost model may also be tailored to a specific sector (e.g. electricity production). As mentioned, these models are not the focus of this study.

run in Cost-Benefit-mode (for example WITCH, see below), but typically 'switch off' the damage cost function. Mitigation cost models are usually run until the year 2050 and may have a global or regional focus.

We use the term "Integrated Assessment Model" only in the context of cost-benefit models (see Box 3).

Box 3: How we use the term "Integrated Assessment Model"

The models are often referred to as Integrated Assessment Models. This is an umbrella term that covers a large and growing variety of numerical models that may conceptually be quite heterogeneous (e.g. mitigation models that "integrate" different economic sectors or cost-benefit models that "integrate" damage and mitigation costs). This heterogeneity reflects the different underlying scientific disciplines, differences in the methodologies and assumptions employed, as well as the different questions or issues models address. The literature does thus not provide a consistent and clear definition of what Integrated Assessment Models are. For that reason, in this study, we use the term in the specific context of cost-benefit Integrated Assessment Models (CB-IAM), unless explicit reference is required. In the damage cost part, we simply use the term damages models. In the mitigation costs part, we partly use the term cost-effectiveness Integrated Assessment Models (CE-IAM) for mitigation costs models in be in line with that literature.

All models require scenario inputs regarding socio-economic factors (e.g. economic growth rate, population growth, emission intensity or technological progress without climate policy) and emission trajectories (see further Section 2.4).

If temperature limits are the model's exogenous constraint, mitigation models — despite not modelling climate damages — still need a carbon cycle and climate sub-model.[11] These sub-models (also called *modules* of the model) translate the temperature limit into emission trajectories, which function as the model's actual endogenous constraints.

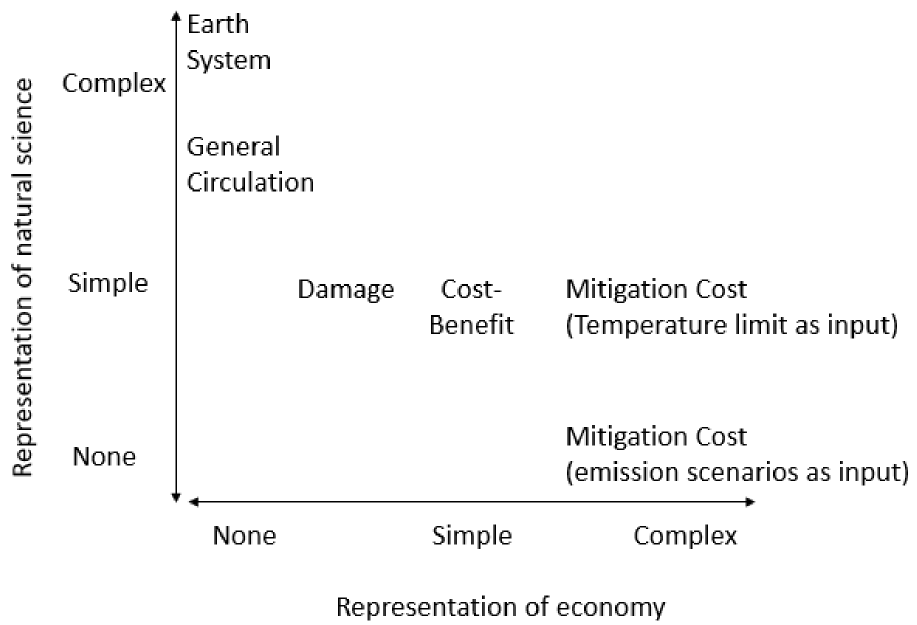
Figure 2 illustrates the differences of the model types with respect to their complexity in the two dimensions *environment* and *economics*. Mitigation cost models represent the *economic* structure in considerable detail, as this is their main purpose. Depending on model input, they also contain a representation of underlying geophysical processes (see above), summarized under the term "natural science" in the figure. Damage cost models usually feature only a simple representation of the economy (mainly connected to the damage function). CB-IAM usually have the same elements as damage models and additionally contain a rather aggregated and simple description of the economy. The figure also depicts Earth System Models[12], which model changes in the *earth system* resulting from emissions of greenhouse gases (they do not consider economic impacts).

Specific models may deviate from this generalised classification. Regardless, no model currently fits in the upper right corner. Combining a complex economic representation with a complex climate (or earth) science model is computationally demanding. And simply combining existing complex models of either domain together is conceptually questionable, as they are built for different purposes.

[11] Most mitigation models use the sub-model "MAGICC" for this purpose, which is a medium complexity model to investigate future climate change and its uncertainties at both the global-mean and regional levels. See further http://www.cgd.ucar.edu/cas/wigley/magicc/ (accessed at 26.10.2020).

[12] Roughly speaking, Earth System Models are General Circulation Models (GCMs) that additionally model the biosphere.

Figure 2: Complexity of different model types



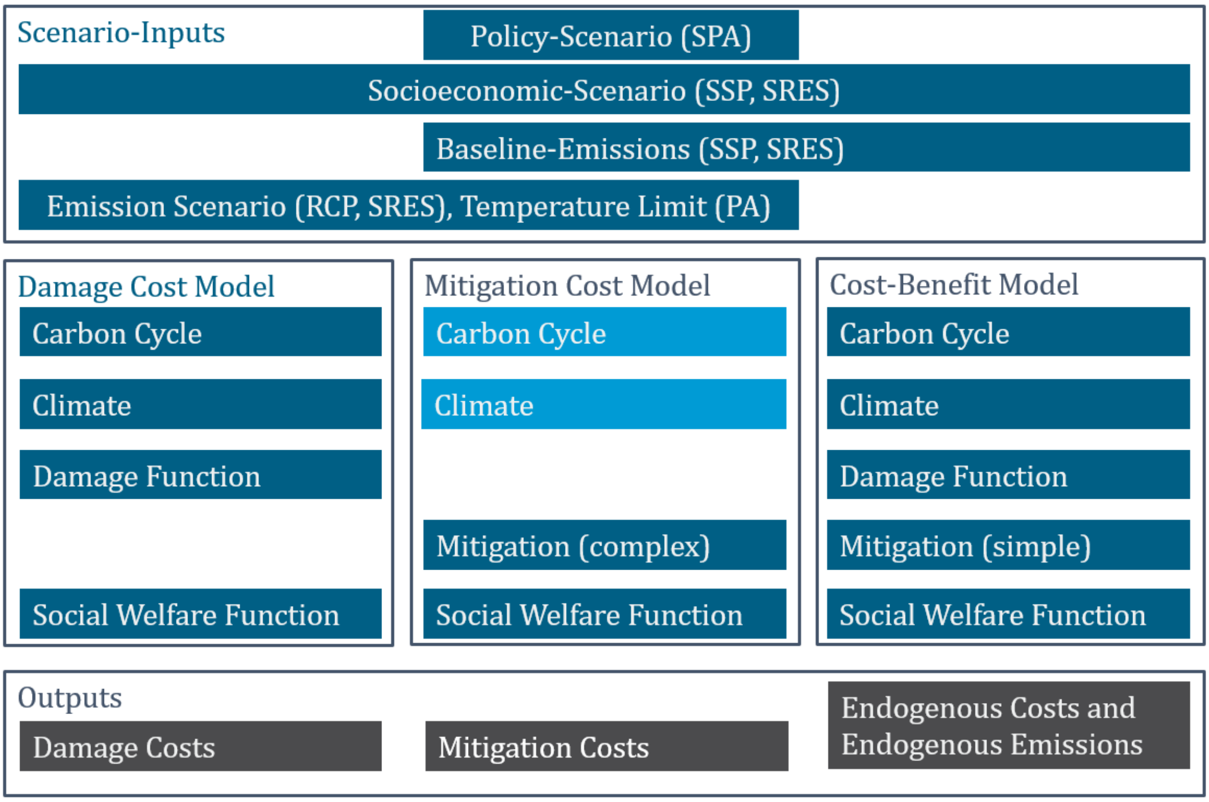
Source: own illustration, Infras

2.2.2 Modules

Figure 3 illustrates the inputs and outputs of the respective models, as well as their modules (i.e. sub-models). Model *inputs* are various scenarios, which are explained in more detail in Section 2.4. The model *output* is the resulting cost estimation (in grey). The modules are:

- A **Carbon Cycle Model** that translates CO_2-emissions into atmospheric CO_2-concentrations.
- A **Climate Model** that translates concentrations of CO_2 and other GHG into climate impacts (temperature and sea level rise).
- A **Damage Function** that determines climate damages (usually expressed in terms of lost GDP) caused by climate impacts. This may include adaptation and its costs.
- A **Mitigation Module** that determines the costs to reduce GHG-emissions.
- A **Social Welfare Function** that evaluates the social utility loss of climate damages and mitigation costs. In mitigation models, this is usually called an *objective function*. For cost-benefit models, it allows to weigh lost consumption from mitigation efforts against future gains in consumption from reduced climate damages.

Figure 3: Inputs and modules of different types of climate cost models



* Strictly speaking, RCP-scenarios relate to GHG-concentration or, more precisely, to radiative forcing.
** As compared to dedicated mitigation costs models, in CB models the mitigation module is rather simplistic
Input scenarios in brackets are commonly used examples that are explained in more detail in Section 2.4.
Source: own illustration, Infras

2.3 Uncertainty and typologies

The overarching question of this report is to work out the most relevant influencing factors that give rise to this uncertainty and assess their significance on the resulting climate costs. There are several possibilities to structure uncertainty related to climate costs. These typologies are partly complementary, and all have their merits and downsides. We thus present several typologies in the following. For the rest of the study, we will correspondingly use the term "uncertainty" in a broad sense, including all those types.

2.3.1 Typology 1: Sources of model uncertainty

There are basically four reasons why climate costs determined by models are uncertain:[13]

- **Parametric uncertainty** concerns the value of the parameters used in models, which may be normative or positive (see typology in Section 2.3.3). Parametric uncertainty is often accounted for by using parameter distribution functions instead of fixed parameter values. However, the respective parameter's distribution is usually unknown too (and hence only approximate).

[13] Gillingham et al. 2016 further list: (a) measurement errors, impacting e.g. the assumed level and trend of global temperatures; (b) algorithmic errors, e.g. algorithms that find incorrect solutions to a model; (c) random errors in structural equations, e.g. those due to weather shocks; (d) coding errors in the model code itself.

- **Inclusion uncertainty** relates to the intended or unintended choice regarding which climate impact categories are monetized and thus accounted for and which are not. The most prominent example is the choice of the sectors that are included in the damage function or whether catastrophic events are considered. This type of uncertainty is usually not accounted for in the quantitative meta-comparison literature. Models tend to get more encompassing, thereby reducing the inclusion uncertainty (but in turn increasing the parametric uncertainty). It is best practice to clearly state the considered impact categories of a model to allow the user to assess the scope reflected by the model's results.

- **Structural uncertainty**[14] relates to which kind of model constitutes the best framework to determine costs. It basically is about the chosen type of equations (their functional forms), the assumptions behind those equations and the effects that are implicitly or explicitly accounted for. It also comprises scientific uncertainty or errors, for example if a model is based on an erroneous theory. Structural uncertainty is a fuzzy category of uncertainty and includes all the uncertainties not captured by the first two concepts. As every model is an (often far-off) approximation to reality, there are myriads of structural uncertainties. Examples range from the neoclassical economic assumptions many models use to the choice of how to account for differences in GDP when aggregating damage costs (not at all, using Purchasing Power Parity (PPP)-adjustments, or equity weighting).

An example for how different sources of uncertainty are interconnected is the so called CES function,[15] which is commonly used in models (as production function or as social welfare function) because of its mathematical tractability. Using the CES function first introduces *structural* uncertainty, since other functional forms are equally plausible but yield different results. Using the CES function then entails setting the value of the elasticity of substitution — its crucial parameter — which in turn inevitably introduces *parametric* uncertainty into the model.

2.3.2 Typology 2: Severity of uncertainty

Uncertainty can be ranked according to its severity with respect to whether the underlying reason is known and whether the probability distribution is known (see Table 2). This typology builds on the dichotomy between "risk" and "uncertainty" as introduced by (Knight, 1921) and extends it to account for tipping points and deep uncertainty.

[14] Also known as model- or specification uncertainty.

[15] CES: Constant Elasticity of Substitution

Table 2: Severity of uncertainty

Type	Underlying reason for uncertainty known?	Probability Distribution function (PDF) known?	Example	Suitable framework
Risk	Yes	Yes	Rolling a dice, playing roulette Note: There is no suitable example in the context of climate change	Expected utility[16]
Ambiguity	Yes	Only incompletely or inconsistently → multiple PDFs	Climate sensitivity, technical progress	Non-probabilistic Approaches 1) Maxmin[17] 2) Minmax regret[18] Multiple PDF Approaches 3) Maxmin expected utility[19] 4) Subjective expected utility[20] 5) Smooth ambiguity model[21]
Tipping points (“known unknowns”)	Partly/unreliably	Essentially unknown	Breakdown of Atlantic meridional overturning circulation	Only qualitatively: 1) Precautionary principle 2) Railguard approaches
Deep uncertainty (“unknown unknowns”)	No	No	Per definition none (only known in hindsight)	

Source: own illustration, Infras. Suitable frameworks partly based on Heal & Millner, 2014.

2.3.3 Typology 3: Uncertainty type

Uncertainty can be connected to an uncertainty type:

[16] Introduced by von Neumann and Morgenstern in 1944

[17] Pick the action whose worst possible outcome (min) is the least bad (max). See Woodward & Bishop, 1997 for an example using DICE.

[18] Pick the action where regret is lowest over all states of the world. Regret focuses on missed opportunities, rather than worst cases. Thus, this rule is less conservative than maxmin. For an application see Lempert et al., 2006.

[19] Actions are ranked according to lowest expected utility (over a plausible set of possible distributions).

[20] Relates to the “ ‘degree of belief,’ to measuring future uncertainties. This approach […] recognizes that it is not possible to obtain frequentist or actuarial probability distributions for the major parameters in integrated assessment models or in the structures of these models. The theory of subjective probability views the probabilities as akin to the odds that informed scientists would take when wagering on the outcome of an uncertain event” (Gillingham et al., 2018, p. 6).

[21] “In the smooth ambiguity model (Klibanoff et al., 2005)there are again many possible distributions consistent with what we know, but in this case, we assign a subjective weight to each distribution. We then use each of the possible distributions to evaluate a policy, and we combine these evaluations into a single value using the subjective weights of the distributions and a flexible measure of ambiguity aversion. The smooth ambiguity approach allows us to use all of the likelihood information contained in the possible distributions. But in order to do this, we need to specify weights for each distribution, and these weights reflect information that is very different from the distributions themselves. The weights are subjective judgments, whereas the distributions are generally considered to be “objective” (i.e., informed by data). The smooth ambiguity model recognizes the necessity of such subjective judgments, in much the same way as the standard SEU [subjective expected utility] framework. However, unlike the SEU framework, the smooth ambiguity model allows us to treat these two kinds of information very differently. That is, by introducing ambiguity aversion, this model preserves the distinction between subjective and objective judgments.”(Heal & Millner, 2014, pp. 132–133).

- **Scientific uncertainty** relates to lacking data and incomplete knowledge of the geophysical and economic aspects that the models try to represent. Climate economic models are — as all models — simplifications of a complex reality and thus need simplifying assumptions to handle the scientific uncertainty. The simplifications are — as far as possible — based on data. Scientific uncertainty is connected to all sources of uncertainty as discussed in Section 2.3.1., e.g. the chosen model set-up or parameter choices such as the climate sensitivity. Scientific uncertainty usually decreases as a function of the total research effort.[22]

- **Normative uncertainty** is introduced by diverging ethical or philosophical judgments. Therefore, an objectively correct value of a normative parameter does not exist. Examples are the choice of the pure rate of time preference or the aversion parameters (see Section 5). It is good practice to transparently discuss the normative basis of a model. That is, in a sensitivity analysis, results should be presented for several plausible sets of normative assumptions such that users can choose results that correspond to their preferences.

- **Scenario uncertainty** relates to the underlying assumptions on future socio-economic and policy developments (e.g. emissions, temperature, population growth, technological change, or new policies). See further Section 2.4.

Box 4: Uncertainty types of general circulation models

General circulation models (GCMs) calculate climate change given a certain emission scenario. They do not include any economics. It is still useful to showcase the types of uncertainty associated with GCMs as there exists a large literature on this topic. It is standard to decompose it into model uncertainty, internal variability, and emissions-scenario uncertainty.

- Model uncertainty refers to the fact that GCMs use different mathematical representations of complex physical and chemical processes governing the climate.

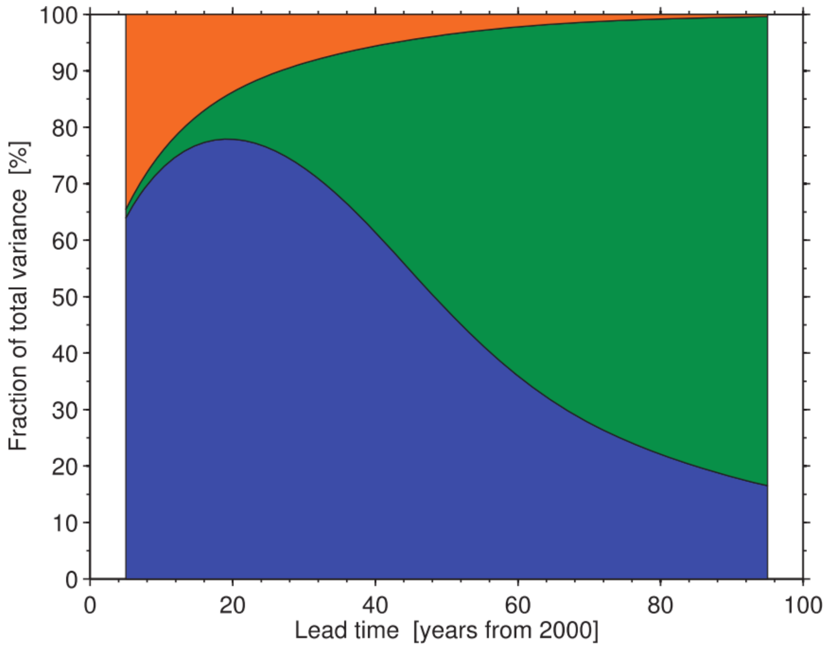
- Internal variability: Climate models are complex and highly nonlinear, and thus prone to chaotic behaviour, meaning that they are sensitive to the initial conditions. Small discrepancies in initial conditions can lead to large differences in the resulting forecasts.

- Finally, there is uncertainty related to the emissions scenarios.

Figure 4 shows that, while for a shorter lead time model uncertainty and initial conditions (internal variability) dominate, in the long-run emissions uncertainty is the greatest source of uncertainty.

[22] Scientific research may also lead to the discovery of new sources of uncertainty. The uncertainty range of the climate sensitivity, for example, remained essentially constant over the last 30 years or so. The intense research led to better data, but also to various previously not considered sources of uncertainty (see further Section 6.2).

Figure 4: Uncertainty types of GCMs



Legend: Uncertainty of GCMs' global decadal mean surface temperature as a function of the lead time with respect to initial conditions (orange), emissions scenarios (green) and model uncertainty (blue).

Source: (Hawkins & Sutton, 2009)

2.3.4 Dealing with uncertainty

Pooling the results of different models is a common and simple method to consider structural uncertainty, as each model provides an alternative representation of reality. However, when aggregating across models, it is important to keep in mind that those models may not be completely independent from each other: Some have common routes, rely on the same fundamental economics or may not account for certain aspects (see e.g. Gillingham et al., 2018, or Howard & Sterner, 2017).

Early damage models have been run deterministically using best-guess values of the uncertain parameters and thus neglected uncertainties. For mitigation models, this is still largely the case. But it is now increasingly considered best practice to run damage models many thousand times using probability distributions for relevant parameters. This stochastic procedure allows to partly account for parametric and structural uncertainty.
Yet, there are different stochastic methods (e.g. different sampling schemes) and the probability distribution of parameters are uncertain. In addition, results have to be summarized to a single estimate or range, for which again different methods exist (handling of outliers, mean vs. median[23], trimming[24], etc.). The impacts of catastrophic events and other

[23] See for example Watkiss, 2011, p. 364, Figure 2,on the difference of median vs. mean values of the SCC.

[24] Trimming relates to the choice of which range ought to represents all results (e.g. interpercentile range of 66% or 95%).

uncertainties are sometimes considered using an ad-hoc surcharge[25] or a stepwise damage function[26].

Finally, for interpretation of scenario results, Huppmann et al., 2018, p. 1029,provide useful guidelines how misinterpretation can be avoided:

- *“Don’t interpret the scenario ensemble as a statistical sample or in terms of likelihood/ agreement in the literature.“*
- *“Don’t focus only on the medians, but consider the full range over the scenario set.“*
- *“Don’t cherry-pick individual scenarios to make general conclusions.“*
- *“Don’t conclude that the absence of a particular scenario (necessarily) means that this scenario is not feasible or possible.“*

This quick overview shows that the handling of uncertainty introduces new uncertainties on its own and that the quantification of uncertainties remains incomplete and contested.

2.4 Scenarios

Scenarios are a common method to deal with the challenge that the future is uncertain. Scenarios are projections of possible future developments in the sense of a “what if” analysis. Importantly, they are no predictions and therefore there are no probabilities attached to scenarios. There are essentially two different types of scenarios:

- System scenarios are internally consistent socioeconomic storylines (e.g. SRES or SSP, see below) or policy assumptions (e.g. SPA). Some system scenarios are qualitative descriptions only. For climate modelling, however, storylines have to be implemented prescribing a set of interconnected parameters, which consider, for example, economic and population growth, technological change, demand side changes, and policies[27].
- Parameter scenarios follow a reverse logic. They prescribe the development of a single parameter, such as (cumulative) emissions, temperature, or GHG concentration. Parameter scenarios may prescribe a political target (temperature limit according to the Paris Agreement), a worst case, or an ensemble of possible futures (e.g. RCP).

Climate cost models usually combine the inputs of both types of scenarios: They use a system scenario as input for the underlying socioeconomic development and a parameter scenario for emissions.

To calculate mitigation costs, it is usually necessary to differentiate between a system scenario that serves as baseline (also known as reference scenario or business-as-usual scenario) and the

[25] For example, the Stern Review (Stern, 2007) using PAGE2002 calculates that climate change reduces average global welfare by an amount equivalent to a permanent cut in per capita consumption of a minimum of 5% (balanced growth equivalents). The Stern Review subsequently cites three aspects that have not been accounted for in PAGE2002: additional nonmarket impacts, climatic response feedbacks, and weighting of regional costs using value judgments. Adding these three aspects, the Stern Review increases its estimate from 5% to 20%.

Another example is DICE-2013R, where William Nordhaus has increased the implemented damage function by a factor 1.25 based on a personal value judgment.

[26] This is the approach used in PAGE.

[27] Policies are sometimes considered in separate sub-scenarios (e.g. SPA-scenarios).

“costly” policy scenarios (with additional climate policy). The baseline scenario is a possible future without any (further) policy intervention. Using a single baseline scenario — as was common until recently — is problematic, as this contradicts the scenario definition in a “what-if” sense. For this reason, several SSP scenarios have been devised, which are all considered as baselines.

To improve comparability across different models, a standardized set of scenarios has been developed that is being used by most climate cost models. These have been devised alongside the IPCC-process and the most up-to-date scenarios are as follows (described in more detail in the following):

- Representative Concentration Pathways (RCPs) prescribe possible radiative forcing projections due to elevated levels of greenhouse gases (see van Vuuren et al., 2011). They are parametric scenarios.
- Shared Socio-economic Pathways (SSPs) describe different qualitative narratives of possible future developments with varying challenges to climate mitigation and adaptation. They do not include explicit climate policies and are thus all baseline scenarios (see Riahi et al., 2017and O’Neill et al., 2017). They are system scenarios.

These scenarios have been primarily designed as inputs into mitigation models. Damage models could use them as inputs for emissions (derived from RCPs) or economic and population growth (SSPs). Yet, many damage models still use older, model-specific, or otherwise different scenarios.

There also exist so called Shared Policy Assumptions (SPA) which have been introduced to improve the comparability of climate policy analysis (Kriegler, Edmonds, et al., 2014) and are in that sense not independent scenarios.[28]

2.4.1 Emission scenarios

Emission scenarios project GHG emissions and thus determine the level of climate change. The currently most used emission scenarios are the Representative Concentration Pathways (RCPs). They feature different trajectories of radiative forcing. Radiative forcing is closely connected to the overall atmospheric concentrations of CO_2 and other greenhouse gases and thus indirectly to emissions. The numerical value of the RCP scenario (e.g. 2.6) corresponds to the level of radiative forcing in W/m^2 in 2100. RCPs do not include any underlying socioeconomic narratives, nor do they prescribe specific emissions of greenhouse gases, albeit it is common to present emissions that are consistent with RCPs for a given model. Note that for the remainder of this study we will use the wording “emission scenarios”, even though RCP-scenarios are strictly speaking radiative forcing scenarios.

Initially, four pathways (RCP2.6, RCP4.5, RCP6.0, and RCP8.5) have been developed. Lately, a fifth pathways (RCP1.9) has been added to account for the 1.5°C target. RCPs have been used in AR5 to provide a consistent framework for the ensemble of global circulation models (CMIP5 ensemble) to calculate the physical impact of climate change. Concerning the *physical impacts* RCP scenarios replaced the SRES scenarios (see Figure 5 and Box 5). The *socioeconomic* component of the outdated SRES-scenarios has on the other hand been replaced by the SSP.

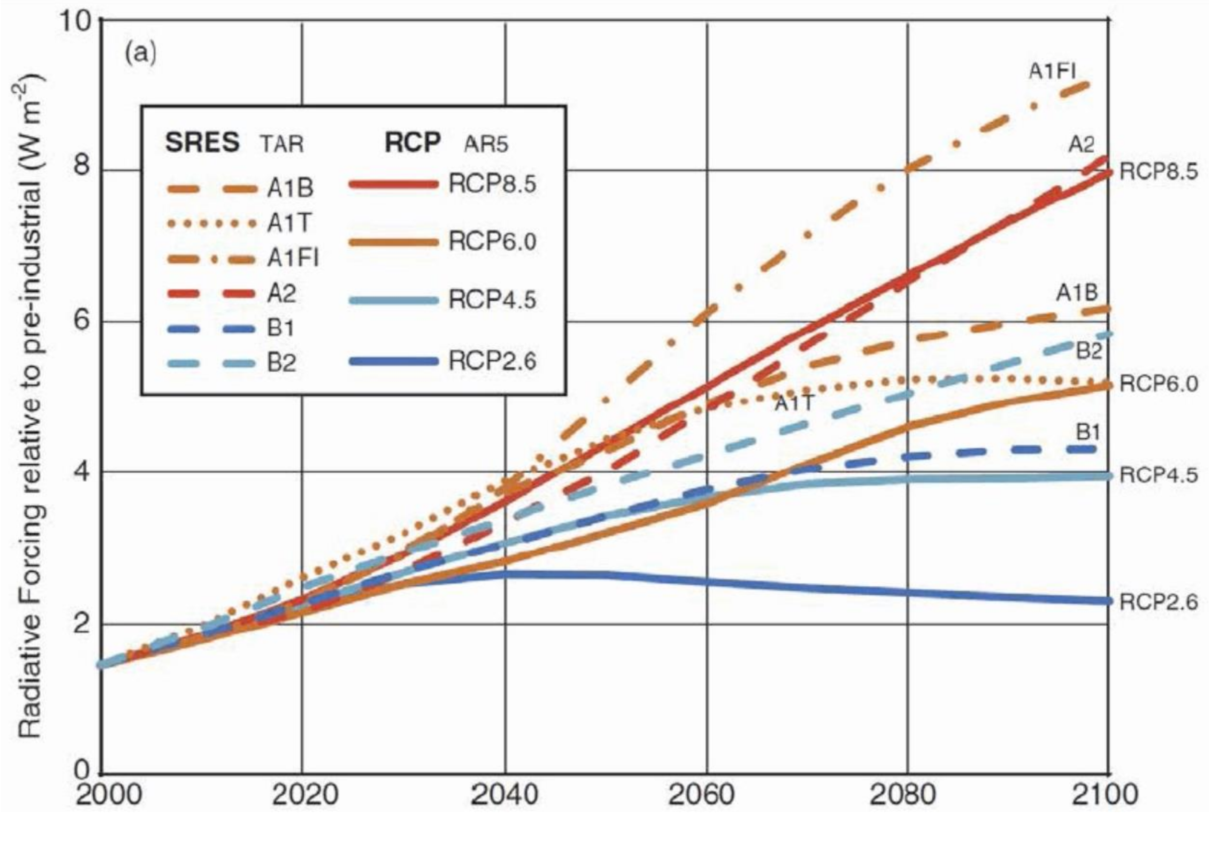
[28] SPAs standardise key policy attributes such as the timing until global cooperation is achieved in the fossil fuel and industry sector or the effectiveness of land-use mitigation. For those attributes, there exist several gradations to make the SPA consistent with the SSP storyline. For example, in an SSP with little global cooperation, global carbon prices will be introduced rather late. Land use policies are assumed to be more difficult to implement in SSPs that are characterized by large inequality and rural/urban divide. For more details on SPAs, see Riahi et al., 2017, Appendix B.

Box 5: SRES-scenarios and the switch to SSP/RCP

The SRES-scenarios have been developed in the 1990s. The name is a reference to the IPCC's Special Report on Emission Scenarios (Nakićenović & IPCC, 2000). The most used scenarios have been A1B, B1 and A2. Damage models often use SRES-scenarios, as these had been state-of-the-art when those models were developed. SRES-scenarios thus still feature in the current literature, since most damage models have not been updated. They might also be used in contexts where comparability with older results is required.

Note that the switch from SRES-scenarios to the new system of SSP/RCP-scenarios involves two fundamental changes: First, RCP-scenarios prescribe atmospheric concentrations of CO_2 and other greenhouse gases, whereas SRES-scenarios prescribe anthropogenic emissions. Second, for the SRES-scenarios, the emissions pathways and the underlying socioeconomic development are convoluted, where in the new system there is a stringent separation between an emissions scenario (RCP; parametric scenario) and a socioeconomic scenario (SSP; system scenario). The switch from SRES to the RCP/SSP-combination is therefore an important change especially for modelling mitigation costs, as it allows to depict more combinations.

Figure 5: SRES and RCP scenarios



Source: IPCC AR5 WGII, Chapter 1

2.4.2 Socioeconomic scenarios

Socioeconomic scenarios project the development of parameters such as economic growth, technological progress, population growth, (baseline) climate policies (and partly emissions of CO_2 and other GHG). The most current scenarios are the SSPs, which complement RCPs by adding underlying socio-economic narratives. There are five SSPs, which are defined based on their degree of challenges to both adaptation and mitigation. Figure 6 shows that there are four scenarios in each corner of this spectrum and there is a scenario placed in the middle. From this starting point, SSPs make different assumptions on economic growth, population growth, fossil fuel and energy demand, food demand, human development, education, urbanisation, lifestyles etc. (see Figure 6), differentiated by regions. Even though these assumptions have a large impact on greenhouse gas emissions they are assumed to occur autonomously. That is, SSPs do not include any explicit climate policy such as carbon prices.

In brief, the five SSPs have the following narrative:[29]

- SSP1 – Sustainability: This storyline assumes the world will move towards a sustainable path, including changes in behavior with a focus on enhancing human well-being. Inequality reduces over time and technological change is directed towards environmentally friendly technologies.
- SSP2 – Middle of the road: in line with historical trends in terms of technological patterns and population as well as economic growth.
- SSP3 – Regional rivalry: world fragmentation and regional rivalry (reversal of globalization trends). The economy remains fossil-fuel intensive, while a lack of global cooperation and a low human development pose high challenges to adaptation.
- SSP4 – Inequality: increasing inequalities and biased technology development. It represents a mixed work, with economic patterns increasing emissions in key regions. In other regions, slow economic development increases the challenges for mitigation.
- SSP5 – Fossil fuel development: robust economic growth and high fossil fuel development driven by an industrialized economy. At the same time, a high level of social and economic development and slower population growth reduces the challenges for climate change adaptation.

[29] This description follows CarbonBrief. For more details see https://www.carbonbrief.org/explainer-how-shared-socioeconomic-pathways-explore-future-climate-change (accessed 18.06.2019)

Figure 6: Key Characteristics of the Five Shared Socio-Economic Pathways (SSPs)

Socio-Economic Challenges to Mitigation	Socio-Economic Challenges to Adaptation		
	Low	**Medium**	**High**
High	**SSP5: Fossil-fuelled development** • low population • very high economic growth per capita • high human development • high technological progress • ample fossil fuel resources • very resource intensive lifestyles • high energy and food demand per capita • economic convergence and global cooperation		**SSP3: Regional rivalry** • high population • low economic growth per capita • low human development • low technological progress • resource-intensive lifestyles • resource-constrained energy and food demand per capita • focus on regional food and energy security • regionalization and lack of global cooperation
Medium		**SSP2: Middle of the road** • medium population • medium and uneven economic growth • medium and uneven human development • medium and uneven technological progress • resource-intensive lifestyles • medium and uneven energy and food demand per capita • limited global cooperation and economic convergence	
Low	**SSP1: Sustainable development** • low population • high economic growth per capita • high human development • high technological progress • environmentally oriented technological and behavioural change • resource-efficient lifestyles • low energy and food demand per capita • economic convergence and global cooperation		**SSP4: Inequality** • Medium to high population • Unequal low to medium economic growth per capita • Unequal low to medium human development • unequal technological progress: high in globalized high-tech sectors, slow in domestic sectors • unequal lifestyles and energy /food consumption: resource intensity depending on income • Globally connected elite, disconnected domestic work forces

Source: Rogelj et al., 2018, p. 110

SSPs are thus narratives "intended as a description of plausible future conditions at the level of large world regions that can serve as a basis for integrated scenarios of emissions and land use, as well as climate impact, adaptation and vulnerability analyses" (O'Neill, Kriegler, et al., 2017, p. 169). To determine the future energy mix and greenhouse gas emissions, mitigation models translate the elements of the SSP storylines into quantitative indicators.[30] The SSPs have been run by six different models[31], generating 24 scenarios (some models only use a subset of SSPs). A reduced complexity climate-carbon cycle model (MAGICC) subsequently converted the emissions into atmospheric concentrations and global mean temperature increases. For the same SSP, results differ among model, as, firstly, different models have different interfaces on how scenario inputs enter the model. Secondly, and more importantly, the models are structured in different ways and make different assumptions about all the relevant influencing factors discussed in Part 3 Mitigation Costs (e.g. technological progress or availability of negative emission technologies).[32]

None of the scenarios is deemed more likely than others and no single SSPs ought to be chosen as baseline, even though the SSP2 "middle of the road" scenario may be tempting in this

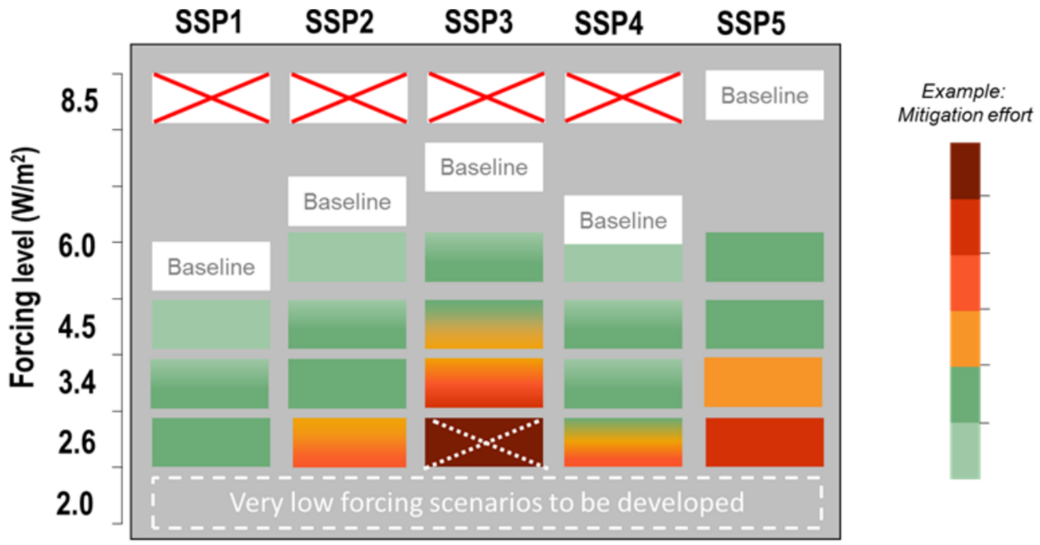
[30] See for example Table 1 in Fricko et al., 2017. Autonomous final energy intensity improvements, e.g., is in SSP1 1.7% per year, in SSP2 1.2% and in SSP3 0.3%.

[31]AIM-CGE ("marker" for SSP3) , GCAM (SSP4), IMAGE (SSP1), MESSAGE-GLOBIOM (SSP2), REMIND-Magpie (SSP5) and WITCH-GLOBIOM (see Riahi et al., 2017, especially the supplementary information).

[32] SSP scenario data is accessible at https://data.ene.iiasa.ac.at/iamc-1.5c-explorer (14.02.2020)

respect.[33] Instead, it is good practice to use all five scenarios as baseline and combine them with RCP-scenarios to obtain a matrix of mitigation efforts. Figure 7 shows that the baselines of SSPs correspond to different radiative forcing levels and that the mitigation effort to reach a given — more stringent — forcing level (i.e. temperature target) thus depends on the SSP scenario. The naming reflects this connection as well. For example, SSP1 "without explicit climate policy" is a baseline scenario called "SSP1-Base". A policy scenario in an SSP1-world aiming at a radiative forcing of 2.6 W/m² is called "SSP1-RCP2.6" (or shorter "SSP1-26") and so forth.

Figure 7: Scenario matrix specified by SSPs and RCP's radiative forcing levels



Legend: Red means more and green less mitigation effort. A red cross means not feasible.
Source: Based on (Riahi et al., 2017)

It is evident that SSPs represent a wide range of possible futures. Yet, as they do not include any explicit climate policy, all SSPs feature a warming of at least 3°C by 2100 and temperatures will continue to increase after 2100, as emissions remain significantly above zero.

[33] Relatedly, the high emission scenario RCP8.5 has often been used as the "business-as-usual" scenario. This is misleading as well, however. See https://www.carbonbrief.org/explainer-the-high-emissions-rcp8-5-global-warming-scenario or Hausfather & Peters, 2020.

3 Policy applications of climate costs

The importance of the costs and benefits of climate policy as a benchmark for governmental and private decisions, has led some governments and other stakeholders to synthesise the debate on climate costs and develop national recommendations for their usage. The legal weight and objective of these recommendations varies among countries. It ranges from

(a) political support for voluntary individual usage (e.g. in the framework of companies' climate risk disclosure, CRD) to

(b) a non-binding orientation guidance (e.g. in Germany) to

(c) a systematic recourse to climate costs in national climate change risk assessments (e.g. in the U.K. under the Labour government), to finally

(d) a binding regulation as part of benefit-cost analyses of environmental policy regulations (e.g. presidential executive order in the US under the Obama administration)

As we show in the following (and in Box 6 and Table 3), governments and other stakeholders use different terminologies for "climate costs", different frameworks (damage costs vs. mitigation costs vs. a mix of both), different assumptions on influencing factors (e.g. discount rates or equity weighting) and thus recommend/prescribe a wide range of values and trajectories.

Box 6: Various terminologies for "climate costs"

Stakeholders use various terminologies for "climate costs". This is either for historical reasons (e.g. "cost rate" is a neutral term used in Germany for various pollutants), related to the context, related to the policy objective, related to the framework, or chosen to convey a certain message (e.g. "value for climate action"). Table 3 provides an overview of the different terminologies.

Table 3: Different terminologies for "climate costs"

Name	Connected to a Framework?	Comment / Explanation	Examples
Social Cost of Carbon (SCC)	Yes (Damages)	Discounted sum of future climate damages caused by emitting one additional ton of CO2 at a given point in time	Price et al., 2007 (for UK) IAWG, 2016 (for USA)
Marginal abatement costs	Yes (Mitigation)	Incremental cost of reducing emissions	Various
Carbon Price	Various	Umbrella term used for "carbon pricing" In the mitigation costs literature partly used in connection to marginal costs	World Bank, several NGOs
Shadow Price of Carbon	Various	Various meanings: - in cost-benefit analyses or impact assessments: assignment of a value to an unpriced commodity (e.g. EBRD) - in economic theory of constraint optimization: marginal utility or benefit of relaxing a constrain (e.g. carbon budget) - Price of externality for economic analysis of investment projects (e.g. World Bank)	EBRD, 2019 Price et al., 2007 (for UK) World Bank, 2017

Name	Connected to a Framework?	Comment / Explanation	Examples
Social Value of Carbon	No	In economic analysis of investment projects: price of induced impact on emissions	(World Bank, 2014)
Cost of Carbon	No	Same as "Social Value of Carbon"	EIB, 2015
Carbon Value	No	No specific definition	DECC, 2009, BEIS, 2019 (for UK)
Social Value of Mitigation Action / Value for Climate Action	Yes (Mitigation)	Benchmark for socially valuable measures and climate policy	Quinet et al., 2019 (for France), Appendix B in Stiglitz et al., 2017
Cost Rate	No	"Kostensatz" in German	UBA, 2019

Source: own illustration, Infras

3.1 United Kingdom

The UK was the first government to recommend a carbon price for use in policy appraisals. In 2002, the UK Government recommended an illustrative estimate for year 2000 emissions of £19/tCO_2, (range £10–£38) using SCC estimates from the Working Group III contribution to the Second IPCC Assessment Report (Cooper et al., 1996) and subsequent studies (Clarkson & Deyes, 2002). These values should be increased at the rate of £1/tCO_2 per year. Subsequently a review (Watkiss et al., 2005) and an update have been issued (Price et al., 2007). In the latter, the carbon price was raised to £25/tCO_2 based on the Stern review, using an emission scenario which leads to stabilisation at 550ppm.[34] In DECC, 2009, a new approach was taken, because of "considerable uncertainty that exists surrounding estimates of the SCC" (DECC, 2009, p. 2). Under this new approach, the SCC is not used any more. The alternative valuation methods differ according to the specific policy objective:

1. For policies in sectors covered by the EU Emissions Trading System (EU-ETS), the „traded price of carbon" is used, based on estimates of future permit prices in the EU-ETS (EUAs). The price for 2020 was set at £7/tCO2 (range £4–£8).
2. For policies in sectors not covered by the EU-ETS estimates are based on mitigation cost estimates. The price for 2020 was set at £16/tCO2 (range £8–£24).
3. In the longer term (2030 onwards), the two prices converge into a single price. The price for 2030 was set at £19/tCO2 (range £10–£29) and for 2050 at £55/tCO2 (range £27–£82).

Note that all ranges are determined adding ±50% (except for point 1).

From 2011 onward (after the change from a Labour to a Conservative government), only the first method has been continued, which is essentially a forecast of the EU-ETS permit prices. Ever since, yearly "short-term traded carbon values used for UK public policy appraisal" are being published.[35] The most up-to-date values are depicted in Figure 8.

[34] The Stern review uses a scenario with higher emissions. Its best guess value of 85$/tCO2 (which equals £53 according to Price et al., 2007, is thus higher.

[35] See https://www.gov.uk/government/collections/carbon-valuation--2 (08.01.2020). The UK also publishes carbon value recommendations for "modelling purposes". Due to different assumptions, these values are lower.

Figure 8: UK short-term traded carbon values for policy appraisal in £$_{2018}$/tCO_2

Year	Low	Central	High
2018	2.33	12.76	25.51
2019	0.00	13.15	26.30
2020	0.00	13.84	27.69
2021	4.04	20.54	37.04
2022	8.08	27.24	46.40
2023	12.12	33.94	55.75
2024	16.17	40.64	65.11
2025	20.21	47.33	74.46
2026	24.25	54.03	83.82
2027	28.29	60.73	93.17
2028	32.33	67.43	102.53
2029	36.37	74.13	111.88
2030	40.41	80.83	121.24

Source: https://www.gov.uk/government/collections/carbon-valuation--2 (08.01.2020)

3.2 France

The French Quinet Commission (Quinet et al., 2019) uses a mitigation cost approach and proposes a "value for climate action" as follows:

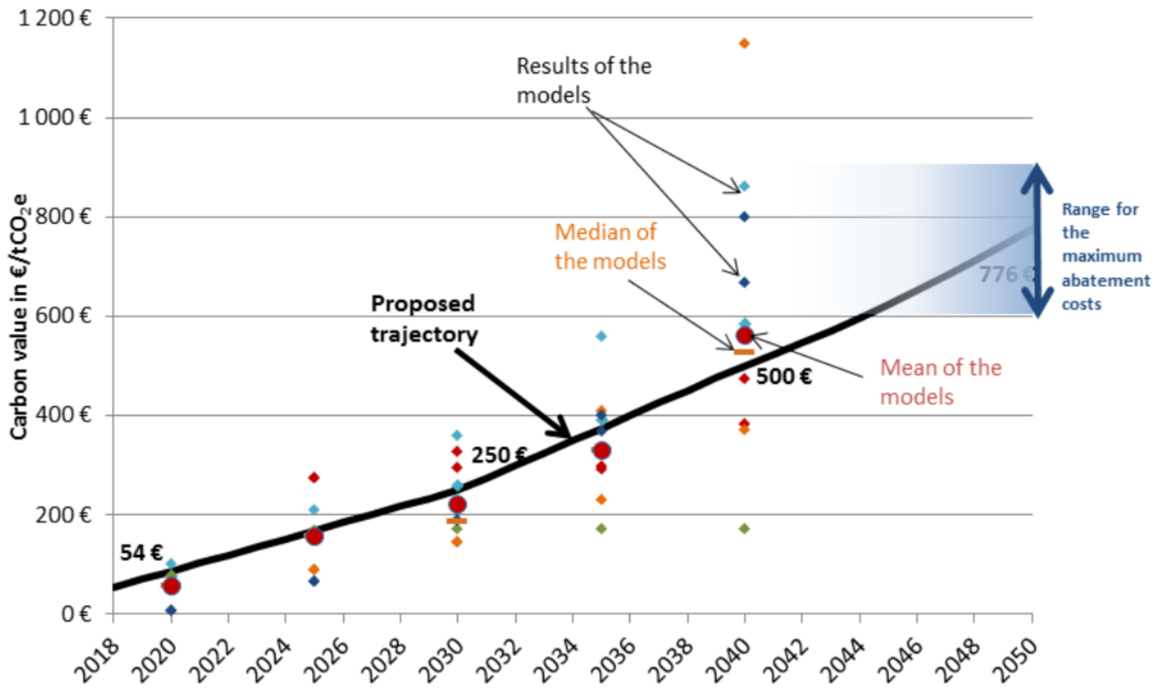
- 2018: €$_{2018}$54/tCO_2eq
- 2020: €$_{2018}$87/tCO_2eq
- 2030: €$_{2018}$250/tCO_2eq[36]
- 2040: €$_{2018}$500/tCO_2eq
- 2050: €$_{2018}$775/tCO_2eq

The climate costs increase rapidly because it is assumed that France decarbonizes by 2050. It recommends regular updates every five to ten years to account for new information.

Until about 2040, emissions have to be cut by 80% (compared to 1990). Up to that point, the price trajectory is directly based on the results of five mitigation models (TIMES-France, POLES-Enerdata, MACLIM-R France, ThreeME and NEMISIS). Afterwards the models' "shadow price increases sharply in all models, and disparities between models increase significantly, expressing the difficulty, even impossibility, of achieving net zero GHG emissions on the basis of mechanisms included in these models alone" (Quinet et al., 2019, p. 90). As a consequence, from 2040 onward, the price trajectory is detached from the models' results. Instead, prices increase at 4.5% per year, in accordance with a public discount rate. The model results and trajectory are displayed in Figure 9.

[36] This value is higher than the previous value €$_{2008}$100 (€$_{2018}$110) given by the commission in 2008.

Figure 9: French "value for climate action" trajectory in €$_{2018}$/tCO_2



Source: Quinet et al., 2019, Figure 38

The idea underlying the value for climate action is that it provides a benchmark to which specific abatement costs of measures and policies can be compared: those measures with lower abatement costs shall then be implemented. If costs are higher, corresponding measures may be postponed or discarded. Crucially, this calculation should consider the climate costs' increasing trajectory along the lifetime of the measure or policy. The value for climate action would thus allow to identify the bundle of to-be-implementable measures and policies which in their sum guarantee that the predefined emission budget is achieved.[37] Note that it remains silent with respect to the (right combination of) instruments the state shall apply to trigger measures (e.g. carbon pricing, subsidies, risk-sharing mechanisms or regulations). As the benchmark increases with time, the scope of measures and policies will be extended as well.

Although useful, we see three limitations with such an approach. First, as also discussed in the Quinet report, mitigation costs must be calculated according to stable, transparent, and standardized rules. This is challenging to guarantee over a heterogeneous set of measures — let alone policies. Second, it is not clear whether the set of possible measures and policies that is being benchmarked is sufficiently comprehensive such that it suffices to achieve the predefined emission trajectory. Third, it is difficult to quantify the interdependencies of policies and measures.

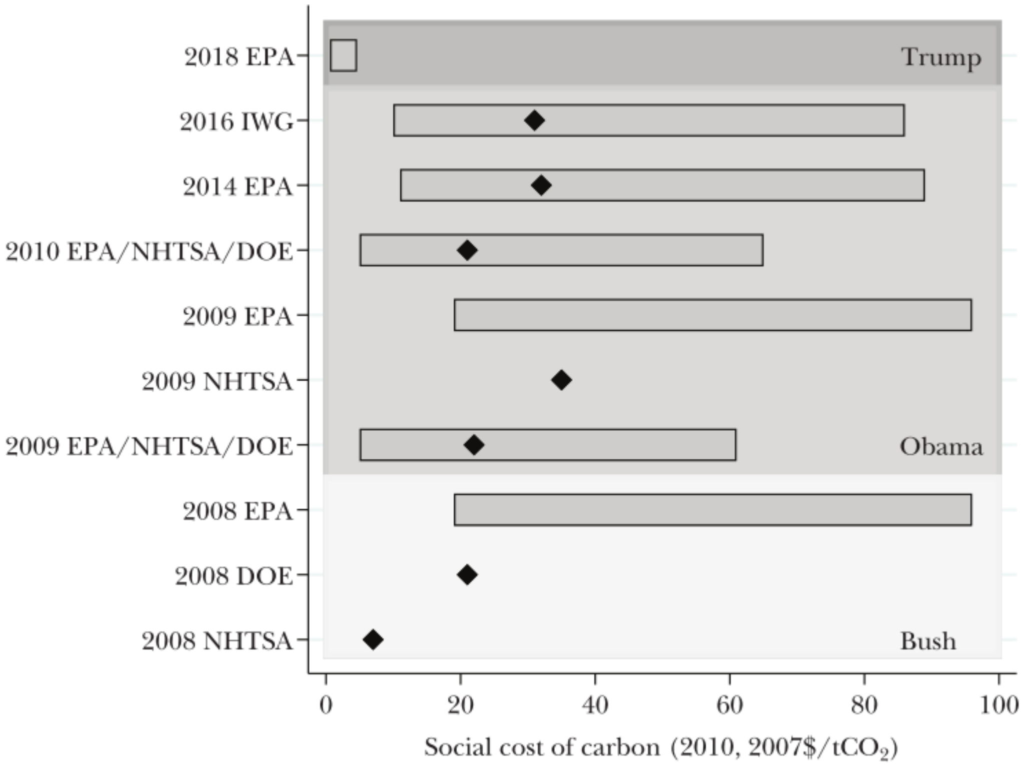
3.3 United States

The US started using climate costs for federal rulemaking in 2008 (see Figure 10). There is an upwards tendency of SCC-values, until the Trump administration used high discount rates and considered only national damages (the latter contradicts the definition of SCC). In the following,

[37] The value for climate action is closely related to the notion of the "switching value" as defined by World Bank, 2017. The switching value is the shadow price of carbon that changes the sign of economic viability of a project.

we thus focus on the results of the Interagency Working Group IAWG, which has been installed by the Obama administration but disbanded by the Trump administration.

Figure 10: US SCC used for Federal Rulemakings in $\$_{2007}/tCO_2$



Notes: Social cost of carbon for emissions of a ton of CO_2 in 2010 in 2007 US dollars. NHTSA is National Highway Traffic Safety Administration; IAWG is Interagency Working Group; EPA is Environmental Protection Agency; DOE is Department of Energy. The black diamond indicates the "central estimate," if one was identified. The grey bars indicate selected upper and lower bounds used in regulatory analyses.
Source: Auffhammer, 2018, p. 35, Figure 1

The IAWG issued three major reports on the social cost of carbon which all use essentially the same methodology. We will thus focus on its most recent 2016 issue (IAWG, 2016). The IAWG additionally mandated the National Academies of Sciences, Engineering, and Medicine to conduct a comprehensive review and recommend updates of the current methodology (National Academies of Sciences, Engineering, and Medicine, 2017).

The IAWG uses FUND, PAGE and DICE to calculate the SCC. All models were run using five scenarios (which are based on the EMF-22 exercise[38] and are described in IAWG 2010) and three fixed discount rates (5%, 3% and 2.5%). That is, the IAWG did not use the Ramsey equation for discounting. They also did not use equity weighting.

Figure 11 show the resulting SCC. All 3 models are run 10'000 times for each of the 5 scenarios, yielding 3x10'000x5=150'000 estimates for each discount rate. The depicted values are the average and the 95%-Percentile of those estimates, respectively. The average is thus across scenarios and models, mixing the respective types of uncertainties. Tables A2-A4 of IAWG 2016 show that — roughly — average estimates by PAGE are twice those of DICE which are in turn twice that of FUND.

Compared to the French trajectory, the IAWG's increase over time is modest.

[38] See also https://emf.stanford.edu/projects/emf-22-climate-change-control-scenarios (08.01.2020)

Figure 11: US SCC Estimates in $2007/tCO2

Year	5% Average	**3% Average**	2.5% Average	High Impact (95th Pct at 3%)
2010	10	**31**	50	86
2015	11	**36**	56	105
2020	12	**42**	62	123
2025	14	**46**	68	138
2030	16	**50**	73	152
2035	18	**55**	78	168
2040	21	**60**	84	183
2045	23	**64**	89	197
2050	26	**69**	95	212

Source: IAWG 2016

3.4 Germany

The German Environment Agency publishes every few years a so called “Methodenkonvention” (MK), which recommends cost rates for several pollutants and GHGs, among them CO_2. The first MK (Schwermer, 2007) was published in 2007 and uses a damage cost approach.[39] The second MK was published in 2012 (Schwermer, 2012) and basically used a mitigation cost approach.[40]

The current MK was published in 2018 (MK3.0). It again uses the damage cost approach and is based on SCC values from FUND, with equity weighting for western Europe (Anthoff, 2007).[41] It recommends 180€$_{2016}$/tCO_2 and a sensitivity analysis using 640€$_{2016}$/tCO_2. The former is based on a PRTP of 1%, the latter on a PRTP of 0%. Values for 2030 and 2050 increase modestly (see Table 4).

Table 4: German cost rates in €$_{2016}$/tCO_2eq

	2016	2030	2050
PRTP=1%	180	205	240
PRTP=0%	640	670	730

Source: UBA, 2019

3.5 European Investment Bank

The European Investment Bank integrates the cost for environmental externalities into the economic analysis of investment projects financed by the bank. The bank provides a central estimate, as well as a lower and upper boundary (see Figure 12). The original source of these

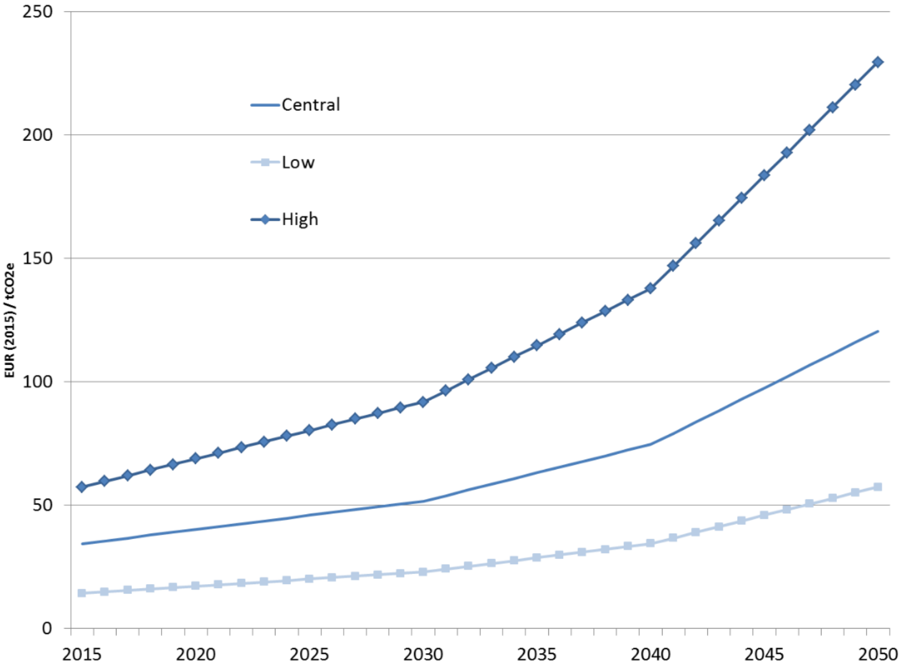
[39] It recommends a best guess cost rate of 70€/tCO2 and a sensitivity analysis using 20€ and 280€. This is derived from a best guess scenario using FUND, with equity weighting and a PRTP of 1%. The high value is based on FUND’s results using PRTP of 0%. The low value is based on a literature review that notes that there is “strong agreement” among experts that the SCC are with “great certainty” above 14€.

[40] It recommends for 2010 a middle value of 80€2010/tCO2, a lower value of 40€2010 and an upper value of 120€2010. For 2030, the middle value increases to 145€2010 (lower: 70€2010, upper: 215€2010). For 2050, the middle value is 260€2010 (lower: 130€2010, upper: 390€2010). These values are based on a meta-analysis of mitigation costs (Kuik et al., 2009a) using the results for a 450ppm CO2 target. The second MK also notes that mitigation costs alone are an inappropriate basis to determine a cost rate. It thus presents SCC estimates using FUND (Anthoff, 2007) with several specification and note that the “orders of magnitude” is similar and thus do not alter the cost rate derived from the mitigation cost approach.

[41] Note that Anthoff, 2007, is based on the emission scenarios EMF14, which stem from 1995. See https://emf.stanford.edu/publications/emf-wp-141-second-round-study-emf-14-integrated-assessment-global-climate-change (09.01.2020). See also Figure 41.

numbers is not stated, such that it is not clear whether a damage cost or mitigating cost framework is used.[42]

Figure 12: European Investment Bank Cost of Carbon in €$_{2015}$/tCO_2



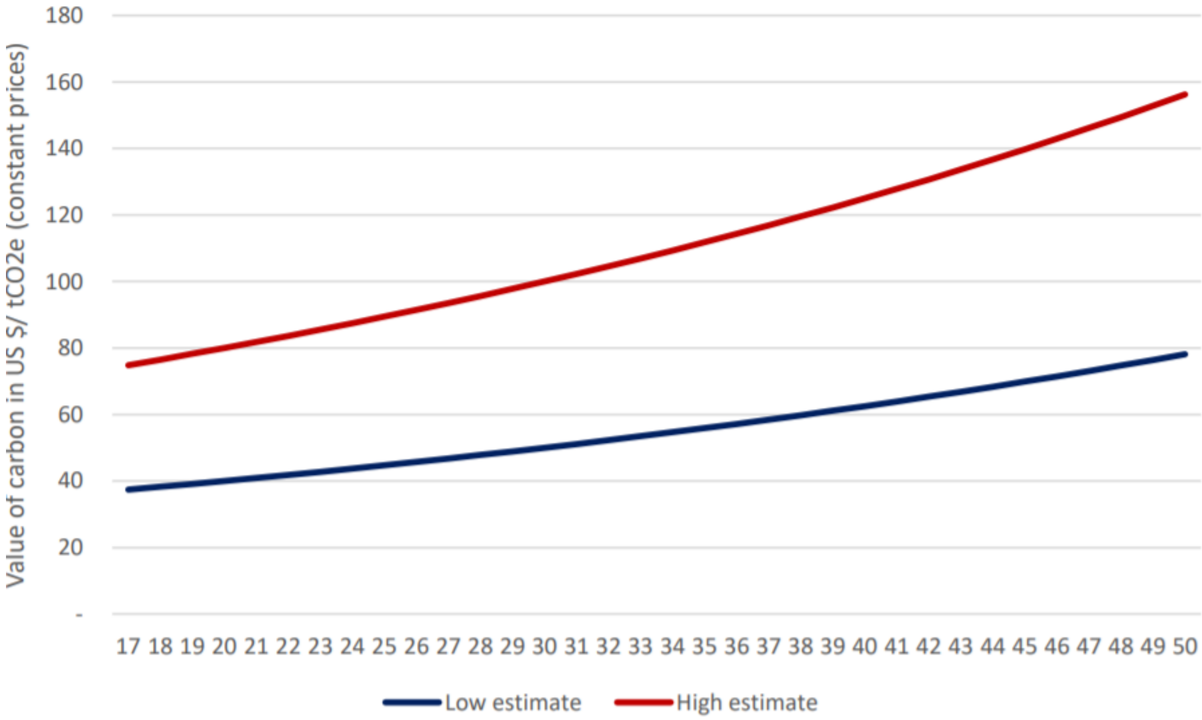
Source: EIB, 2015

3.6 World Bank

The World Bank regularly issues guidance notes aimed at valuing carbon savings of investments. Like for the European Investment Bank, this serves to account for environmental externalities in investment decisions. While the last guidance of the year 2014 was based on SCC and mitigation costs, the most up-to-date version (World Bank, 2017)is only based on mitigation costs. With this, the current guidance follows the recommendations of the “Report of the High-Level Commission on Carbon Prices” (Stiglitz et al., 2017). This report takes the goal of the Paris Agreement as given and assesses “technological roadmaps, analyses of national mitigation and development pathways, and global integrated assessment models, taking into account the strengths and limitations of these various information sources.” (p. 2). It concludes that to achieve the Paris Agreement’s goal, a carbon price of at least 40–80$/t$CO_2$ by 2020 and 50–100$/tCO2 by 2030 is needed, assuming that a “supportive policy environment is in place” (p. 3). From 2030 onwards, the World Bank extrapolates these lower and upper bounds using a growth rate of 2.25% for each.

[42] The values are based on an “extensive review conducted for the Bank by the Stockholm Environmental Institute in 2006”, yet this study is not available.

Figure 13: Shadow price of carbon in US$$_{2017}$/t$CO_2$



Source: World Bank, 2017

3.7 Overview

Table 5 provides an overview of the various climate costs that are recommended or prescribed for policy applications by the various stakeholders. To improve comparability, we normalized the price to €2019 values.

Most stakeholders use a mitigation framework in the most up-to-date recommendations. The UK and the World Bank switched from (partly) SCC-based to mitigation-based estimates (not shown). The US and Germany base their estimates on SCC.

Values for the year 2020 are in the range of approximately 35–70€$_{2019}$. Two outliers are, on the low end, the UK 2019 estimate (which is, however, merely a prediction of the EU-ETS price) and, on the high end, the German recommendation (for PRTP=1% this is probably due to the usage of equity weighting). All estimates increase with time. The French recommendation's trajectory is especially steep, overtaking the German one before 2030.

Table 5: Costs rates in various countries normalized to €2019

Country	Assumption / Setting	Framework	Climate Cost (€/tCO2) by			Reference
			2020	2030	2050	
UK	Non EU-ETS	Mitigation	35 (17-52)	41 (22-63)	119 (58-177)	BEIS, 2019
UK	EU-ETS	Mitigation	16 (0-32)	93 (46-139)	NA	BEIS, 2019
France	Decarbonization by 2050	Mitigation	85	254	786	Quinet et al., 2019
US	Before Trump-Administration	Damage	36 (10-106)	43 (14-130)	59 (22-182)	IAWG 2016
Germany	PRTP=1%	Damage	189	215	251	UBA, 2019
Germany	PRTP=0%	Damage	671	702	765	UBA, 2019
European Invest. Bank	Unclear	Unclear	47 (21-74)	55 (26-95)	126 (58-242)	EIB, 2015
World Bank	Goals of Paris Agreement	Mitigation	37-73	46-92	71-143	World Bank, 2017

Source: own illustration, Infras. Data: see references. For original values see Table 45 in Appendix B. For normalization to €2019, we first used the current exchange rate[43] to convert into €.[44] Second, we used the German consumer price index[45] to calculate €2019 values.

[43] See https://unctadstat.unctad.org/wds/TableViewer/tableView.aspx?ReportId=117 (21.01.2020)

[44] An alternative option is to use PPP correction factors to convert currencies. As all values stem from developed countries, the difference between the two approaches is small.

[45] See https://www-genesis.destatis.de/genesis/online/data?operation=previous&levelindex=1&step=1&titel=Ergebnis&levelid=1579615135618&acceptscookies=false (21.01.2020)

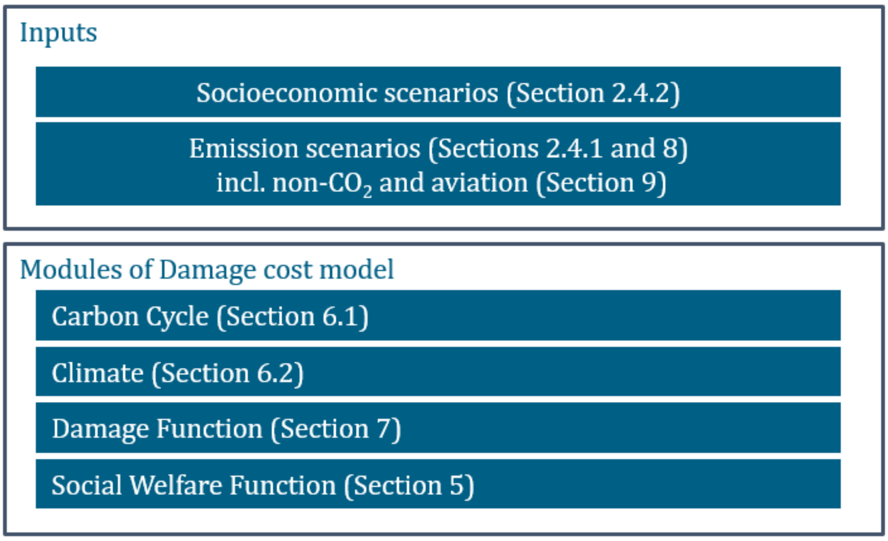
Part 2: Damages costs

This part of the study focuses on damage costs and is structured as follows. Section 4 provides an overview and a structure of relevant influencing factors for damage cost estimates. In Sections 5–9 we analyse those factors in detail. In Section 10, we briefly discuss cost-benefit models. Section 11 provides a history of damage models and Section 12 presents the "default" version (as designed by the original developers) of the three arguably most commonly used damage models (DICE, FUND and PAGE). In Section 13, we present a quantitative impact assessment using literature results as well as numbers we generated specifically for this study. Section 14 briefly exemplifies a specific expert survey as an alternative way to derive damage cost estimates. Finally, Section 15 summarizes the damage costs findings.

4 Overview on influencing factors and related uncertainties

Damage models estimate the social costs of carbon (SCC) using the modules as presented in Section 2.2.2. These modules are again highlighted in the following figure.[46]

Figure 14: Modules and inputs of damage models



Source: own illustration, Infras

In a nutshell, the amount of emitted GHGs determines how the atmospheric composition changes (Carbon Cycle Model) and subsequently how the climate changes (Climate Model). The reaction of the climate system with its numerous feedback effects then leads to climate impacts. Impacts vary from region to region and affect various ecosystems, as well as social and economic areas (directly or indirectly). Moreover, there exist a variety of adaptation measures that alleviate impacts. Using the damage function, these corresponding impacts are then monetized. Subsequently, the damages are aggregated across time and space using the Social Welfare Function (SWF). All those steps include varying levels of uncertainty.

Note that numerous meta-studies exist that discuss influencing factors of the SCC and climate cost modelling in general. Examples are (Stern, 2007), Ortiz & Markandya, 2009,, Tol, 2009, Watkiss, 2011, Ackerman & Stanton, 2012, Stern, 2013, Van den Bergh & Botzen, 2015, Gillingham et al., 2018, Weyant, 2017, Heal, 2017, IAWG, 2010, Farmer et al., 2015, IAWG, 2016, Rose et al., 2014, National Academies of Sciences, Engineering and Medicine (NASEM), 2017, (Howard & Sterner, 2017), Economides et al., 2018, Tol, 2018, Nordhaus, 2018, or Pindyck, 2019. This study heavily draws from these contributions.

[46] For didactical reasons, the order is slightly different than in Figure 7.

5 Social welfare function

A social welfare function (SWF) allows to aggregate damages across space and time[47]. It measures well-being at an aggregate level and has the unit “utils”. It is a function of consumption.[48] Usually, the SWF is expressed using a simple iso-elastic form: [49]

$$SWF = \frac{1}{1-\eta}\int_0^\infty C_t^{1-\eta} e^{-\delta t}\, dt$$

where C_t is the global consumption at time t, η the elasticity of marginal welfare of consumption (i.e. the percentage change in marginal welfare per percent change in consumption) and δ is the pure rate of time preference (PRTP). This represents the discount rate that applies to future welfare changes. An iso-elastic function is common because the elasticity of marginal welfare with respect to consumption is independent of the consumption level (that is it always equals η). It is thus mathematically more tractable. An important feature of the SWF is that marginal welfare decreases: at lower levels of consumption the marginal welfare of consumption is higher than for higher levels. This represents the notion that an additional dollar is worth more for a poor person than for a rich one.

Discounting and equity-weighting are the two main influencing factors that directly relate to the SWF and are discussed as follows:

5.1 Discounting: aggregation across time

Arguably the most important influencing factor concerns intergenerational equity. It relates to the question which weight future generation’s damages ought to receive. Economists answer this question by discounting the future’s consumption (see Dasgupta, 2008 for an overview). The higher the discount rate, the lower the value of future consumption as compared to the current one. The discount rate plays an extremely important role in the economic assessment of climate damage in the future, as the climate impacts of GHG emissions persist and accumulate over very long periods and may even be irreversible (Solomon et al., 2009). The present value of future climate damages (and thus the SCC) is strongly dependent on how much a society values these distant future impacts and the corresponding consumption losses. In a cost-benefit setting, discounting additionally allows to compare mitigation costs (which rather occur in the short term) with avoided damages (which rather occur in the long term).

Note that models necessarily consider damages only for a limited time horizon. If the discount rate is low, the choice of the modelled time-period may have a significant influence on the results. If the discount rate is high, on the other hand, the cut-off year becomes less relevant.

There are three common discounting schemes:

- A **fixed discount rate** prescribes a discount rate that remains constant with time. This is the simplest scheme (see Section 5.1.1).

[47] It also allows to compare costs and benefits from mitigation efforts in a CB-IAM. The optimum of an CB-IAM corresponds to the state where the welfare (also called utility or well-being) is maximized.

[48] Parts of the literature use “utility” instead of “welfare”. In our context, the two concepts are interchangeable, and we thus use “welfare”. As unit of the SWF we nevertheless use “utils” as this is common practice in the literature.

[49] This SWF is globally aggregated. We will discuss a SWF that differentiates between different regions in Section 5.2, which deals with equity weighting.

- **Ramsey discounting** is a frequently used scheme. It combines several reasons for discounting (pure time discounting, inequality aversion and in some cases risk aversion) and leads to a discount rate that varies with time (see Section 5.1.2).
- A **declining discount rate** implies that the discount rate declines with time using a predefined trajectory (see Section 5.1.3).

5.1.1 Fixed discount rate

A fixed discount rate remains constant over time. It is important to note that already a seemingly low discount rate renders the far future unimportant and that small differences in the discount rate make large differences in the long term. To see this, consider the following example: A future damage of 100€ at a discount rate of 3% (1%), if it occurs

- in 50 years has a present value of 22.8€ (60.8€),
- in 100 years has a present value of 5.2€ (37.0€), and
- in 200 years has a present value of 0.3€ (13.7€).

As a further illustration, assume there is a constant stream of yearly damages (e.g. 100 $ per year) for 300 years. Table 6 shows the share of discounted damages that fall into a certain time period. For reference, note that a discount rate of 0% corresponds to the situation without discounting. It is evident that for discount rates of 3% and above, the time period after 60 years from now has little influence on the present value of damages.

Table 6: Illustration of share of discounted damages per time period for a constant stream of yearly damages

Discount rate Time period	0%	1%	2%	3%	5%	7%
0-30 years	10%	27%	45%	59%	77%	87%
31-60 years	10%	20%	25%	24%	18%	11%
61-90 years	10%	15%	14%	10%	4%	1%
91-120 years	10%	11%	8%	4%	1%	0%
120-300 years	60%	27%	9%	3%	0%	0%

Source: own illustration, Infras

In Table 7, we modify the illustration and use a stream of increasing yearly damages based on the temperature increase and corresponding damages as provided by DICE-2013R from 2000 until 2300 (see Section 12.1).[50] Percentages in this example refer to damages as a fraction of GDP. In this setting, the majority of damages occurs after 100 years (see again the case with a discount rate of 0%). Yet, for discount rates of more than 3%, the share of *discounted* damages for later periods is still small.

[50] We used parameters as given by the Mimi-Version (seel further Section 12.1.4). The temperature increases with time and damages increase quadratic with temperature (according to DICE-2013R damages are proportional to $0.00267*\Delta T(t)^2$).

Table 7: Illustration of share of discounted damages per time period for increasing yearly damages as given by DICE-2013R (damages as fraction of GDP)

Discount rate Time period	0%	1%	2%	3%	5%	7%
0-30 years	0%	2%	8%	17%	40%	61%
31-60 years	2%	6%	14%	23%	31%	27%
61-90 years	4%	10%	18%	23%	18%	9%
91-120 years	7%	14%	19%	17%	8%	2%
120-300 years	87%	67%	42%	21%	4%	1%

Source: own illustration, Infras

Finally, in Table 8, we multiply the above damages fraction with the global GDP levels as projected by DICE-2013R. This results in absolute damages. As GDP rises exponentially, yearly absolute damages are very high in later periods, hence they dominate total damages: for a discount rate of 0%, the first 120 years make up only 4% of total damages. Correspondingly, even for a discount rate of 5%, a non-negligible share of the discounted damages accrues in later periods. The fundamental reason is that the effect of (exponential) discounting is roughly balanced by exponential GDP-growth.

Table 8: Illustration of share of discounted damages per time period for increasing damages as given by DICE-2013R (absolute damages)

Discount rate Time period	0%	1%	2%	3%	5%	7%
0-30 years	0%	0%	3%	3%	15%	35%
31-60 years	0%	1%	4%	10%	26%	34%
61-90 years	1%	4%	9%	18%	26%	20%
91-120 years	3%	8%	15%	21%	18%	8%
120-300 years	96%	87%	70%	48%	15%	3%

Source: own illustration, Infras

In this last case, the future receives the more weight, the faster the global economy grows. To account for this rather awkward result, models usually apply the so-called “Ramsey discounting” instead of using a fixed discount rate like in the previous examples. Ramsey discounting is presented next.

5.1.2 Ramsey discounting

Damage models usually do not use a fixed discount rate but derive it instead according to the framework set up by (Ramsey, 1928). From the SWF as described above, the so-called **Ramsey Equation** can be derived:

$$\rho = \delta + \eta * g$$

where

- ρ is the social discount rate (SDR)
- δ is the pure rate of time preference (PRTP),
- η is the elasticity of the marginal utility of consumption, and
- g is the annual growth rate of per capita consumption.

Note that the PRTP is the rate at which future *welfare* changes are discounted, while the SDR is the rate at which future *consumption* changes are discounted. Climate damages imply consumption losses such that the SDR is the appropriate discounting rate in this setting. According to the Ramsey Equation, the SDR has two components:

- **Time discounting:** The first component is the PRTP, which is the rate at which future welfare changes are discounted. According to this component, the future is discounted because its welfare counts less.
- **Growth discounting:** The second component is the product of η and g. If g is positive, future generations are richer than the present one. In combination with η (which in this context represents the intergenerational inequality aversion), the present value of future consumption losses decreases, as it increases the SDR. Growth discounting thus gives rise to policies that tend to increase current and decrease future consumption.

No parameter of the Ramsey Equation is observable, and its values are fiercely debated. Some studies assume that the behavior of individuals or the financial market provide insights into the social preferences and offer guidance in estimating (or calibrating) δ or η based on empirical evidence (e.g. Nordhaus, 2007). Others argue that a descriptive approach is not appropriate, as empirical evidence is based on short-term behavior and influenced by factors that are not related to climate change (e.g. monetary policy). On a more philosophical note, some argue that it is illegitimate deducing an “ought” from an “is”.[51] Instead this strand of the literature argues that δ or η are normative and thus require an explicit ethical justification (e.g. Stern, 2007, Heal & Millner, 2014,Heal, 2017).

Due to these fundamentally different views, the SDR exhibits a large range in the literature. Table 9 synthesizes the relevant literature and provides an overview of the elements introduced above. In addition, some stakeholders also use fixed discount rates as introduced in Section 5.1.1. The US Interagency Working Group uses a fixed discount rate of 2.5%, 3% and 5% and the US Office of Management and Budget (2003) uses a fixed discount rate of 3–7%, based on financial market observation (descriptive approaches).

[51] This was for the first time brough forward by David Hume (1711—1776).

Table 9: Social discount rate and related parameters

Author	δ Pure Rate of Time Preference	η Elasticity of Marginal Utility of Consumption	g Annual per Capita Growth Rate	ρ Social Discount Rate (derived from Ramsey equations)
Cline (1992)	0%	1.5	1%	1.5%
IPCC (1996)	0%	1.5-2.0	1.6-8%	2.4-16%
Arrow (1999)	0%	2	2%	4%
UK Green Book 2018	1.5%	1	2%	3.5[a]
France: Rapport Lebègue (2005)	0%	2	2%	4%*
Stern (2007	0.1%	1	1.3%	1.4%
Arrow (2007)		2-3		
Dasgupta (2007)	0.1%	2-4		
Weitzmann (2007)	2%	2	2%	6%
Nordhaus (2008)	1%	2	2%	5%

* Decreasing with the time horizon.

Source: IPCC's Assessment Report 5,, Working Group 3, chapter 3 (Kolstad et al., 2014, p. 230, Table 3.2). UK Green Book: updated numbers from HM Treasury, 2018. Authors as given in the original sources.

When estimates of SCC are reported, they are often presented for different PRTPs only. Yet, even for similar PRTPs, the SDR can vary considerably because — as shown in Table 9 — the influence of other parameters is equally relevant. These parameters should thus also undergo a strict sensitivity analysis and their chosen values should subsequently be made transparent.

In the following, we discuss the parameters of the Ramsey Equation and the way they enter models in more detail:

5.1.2.1 Pure rate of time preference PRTP (δ)

A recent expert survey with 208 participants showed a median value of 0.5% for the PRTP (Drupp & Hänsel, 2018). The majority of studies cited in Table 9 assume a value of (or close to) zero, basically due to the normative argument that all generations' welfare ought to be given equal weight to calculate social welfare. Discounting the future is, in this logic, only applicable because there is a risk of extinction due to things unrelated to climate change (Stern, 2007) or because δ=0 would imply an extreme moral burden for the present (e.g. Cline, 1992 ,Stern, 2007 or Ramsey, 1928). Another strand of the literature argues that δ ought to be based on the observed behavior of actors in the market (e.g. Nordhaus, 2007). Therefore, some studies in Table 9 apply δ=1.5 or δ=2. Such high values assume that intergenerational, long-term considerations can be derived from rather short-term market behavior.

Interest rates as determined by the market depend on monetary policy and reflect the supply of savings versus the demand for financing. These are issues unrelated to climate change policies. Financial interest rates also depend strongly on the risk level associated with the asset in question. In addition, the above cited discussion in the literature stems from before the financial crisis. In its aftermath, central banks lowered interest rates substantially and as of 2020, they are still at historically low levels and even negative in some countries. These aspects question the validity of the market approach in the climate change context per se. In particular, they question the derivation of high discount rates and their use in climate cost modelling.

5.1.2.2 Growth rate of per capita consumption (g)

There exists a large body of literature on the theory of economic growth rates.[52] Yet, a reliable forecast of long-run economic growth rates is not possible (Heal & Millner, 2014, Millner & McDermott, 2016). This is unsettling because the growth rate has a strong influence on the discount rate. Models usually assume that economies grow indefinitely — albeit at decreasing exponential rates. Per capita GDP growth rates are either taken from exogenous socio-economic scenarios (e.g. in the FUND and PAGE) or determined endogenously (e.g. DICE).

Note that a small difference in the growth rate makes a huge difference in the long term. Assume that GDP at time zero equals 100. After hundred years, a per capita growth rate of GDP g=1% / 2% / 3% implies a GDP of 270, 724 and 1922, respectively. Therefore, if the growth rate is high, future generations will be much richer than the present one. In combination with inequality aversion, the present generation thus gives consumption losses of its much richer descendants a low value. Put differently, the present generation will have little incentive to invest in costly mitigation efforts to increase future generations' consumption.[53]

5.1.2.3 Elasticity of marginal welfare of consumption (η)

In this context η represents intergenerational inequality aversion.[54] It is likewise a normative parameter, such that there is no objectively correct value.

The value of η may be estimated from empirical sources, such as income tax schedules, asset markets, and behavioral surveys(Heal & Millner, 2014). This data is, however, associated with an aversion to *intra*-generational inequality (i.e. between individuals *within* a generation) and thus arguably not appropriate for *inter*generational inequality. Inequality aversion values typically range between 0.5 and 2.5 (Anthoff et al., 2009; Douglas J. Arent et al., 2014; Pearce, 2003), but there are also studies which explore larger values, as seen in Table 9. Therefore, η=1.5 may be a reasonable starting point, with values between 1 and 3 recommended for sensitivity analysis.

If GDP per capita in the future is a factor x of the present's, the future's marginal welfare is a factor 1/(x*η) of the present's (using the isoelastic social welfare function). The future weighs accordingly less in any welfare consideration.

To see this more clearly, consider two generations, poor and rich, with annual consumption of 360 and 36,000, respectively.[55] If η=2, a decrease in poor's consumption of 1% (i.e. 3.60€) would be equivalent in terms of welfare to a decrease in rich's consumption of 50% (i.e. 18,000€). If η=3, for the same decrease in poor's consumption, the rich's consumption would need to decrease by 93% (33,480€). In other words, if η is high, a small reduction in consumption for the poor leads to a welfare loss comparable to the rich losing almost their entire consumption.

[52] Growth rates always refer to real GDP and not nominal GDP. The latter includes inflation, which is not relevant in this context.

[53] This line of reasoning assumes that there is only one type of consumption, which is influenced by both economic growth and climate damages. This is highly contested in the literature (see further Section 7.3).

[54] The elasticity of marginal welfare may also represent risk aversion and intragenerational inequality aversion (see Box 8 in Section 5.3).

[55] The example is based on (Dasgupta, 2008).

Therefore, together with the assumption of eternal economic growth (that is, the present being "poor" and the future being "rich"), intergenerational inequality aversion results in a low present value of future consumption losses.

5.1.2.4 Ramsey equation under uncertainty

The future growth rate is highly uncertain, especially over the long time periods concerning climate change. As a corollary, the growth discounting part of the Ramsey equation is equally uncertain. If growth deviations are independent and identically distributed (IID), an **extended Ramsey Equation** can be derived (see Gollier, 2010 or Arrow et al., 2014):

$$\rho = \delta + \eta E(g) — 0.5\eta^2\sigma_g^2,$$

where E(g) is the expected value of the growth rate and σ_g^2 is its variance. Note that in this setting, it is not relevant whether the uncertainty is due to climate change or due to other factors. The third term is the extension and introduces a precautionary effect. A higher variance (a measure of risk) decreases the social discount rate. For this third term, η is to be interpreted as the *risk* aversion and the social discount rate decreases with increasing η due to this term alone. This contrasts with the second term, where η is a measure for *inequality* aversion and the social discount rate increases with *increasing* η. It is common to depict both concepts with the same parameter. In the context of climate change, this approach is arguably inappropriate, as it conflates the two inherently different concepts (Van den Bergh & Botzen, 2015). For an evaluation of social welfare, it is perfectly reasonable to assume a low inequality aversion with respect to future generations and at the same time a high-risk aversion with respect to climate damages or vice versa. On the multiple roles or η see also Box 8 in Section 5.3.

5.1.3 Declining discount rates

Weitzman, 2001and others[56] argue that a declining SDR ought to be used. They show that this is the best approach to represent people's varying preferences with respect to the parameters underlying the Ramsey Equation. Maximizing a weighted sum of people's welfare, it can be shown that this is equivalent to using a representative agent, whose SDR declines with time (and asymptotically approaches the lowest discount rate existing in the population).

The reason for this is as follows: Assume that three people's preferences are 1%, 3% and 5%. In the long run, the discount rate of 1% will dominate the overall result. In the short run however, the influence of each of the three values is roughly equal, yielding an average discount rate of 3%.[57]

For that reason, the U.K. Green Book proposes that for policies or projects which involve long-term effects, a declining discount rate should be used (see Table 10).

[56] This idea has been extended by e.g. Gollier & Weitzman, 2010 or Heal & Millner, 2014. For an overview see Heal, 2017.

[57] Another justification for a declining discount rate is as follows: If random shocks to growth are positively correlated over time, i.e. occur more and more frequently in the future, the last term in the extended Ramsey equation will also lead to a declining discount rate over time (for a detailed derivation see Gollier, 2010).

Table 10: Declining discount rate according to UK Green Book

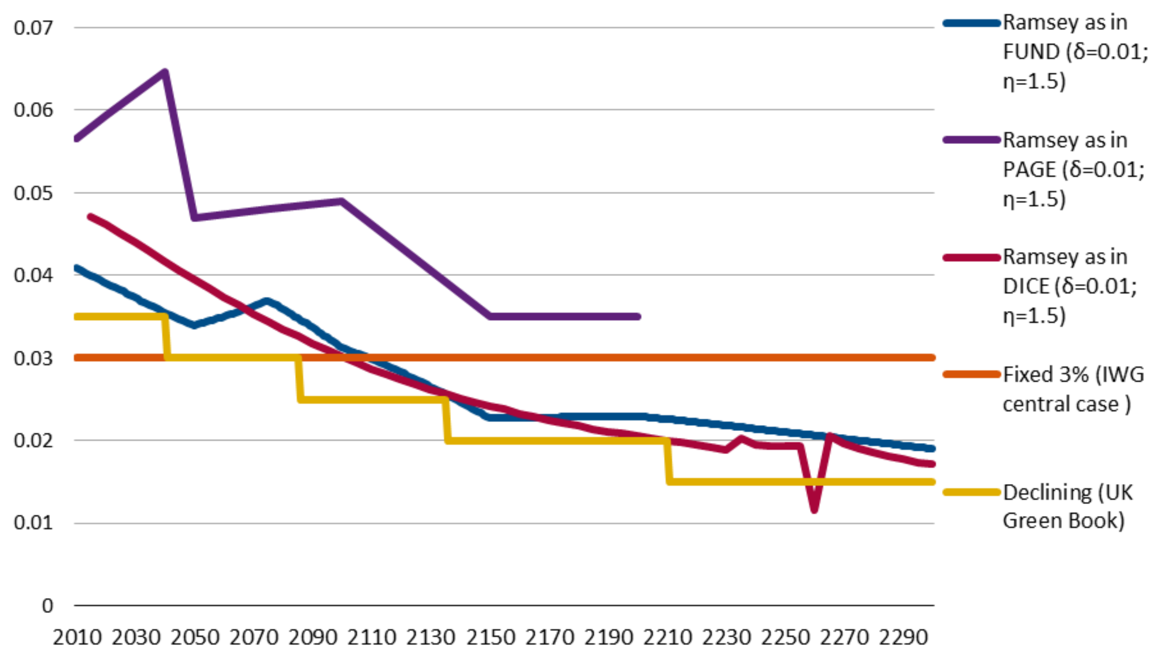
Period of years	Social Discount Rate
0-30	3.5%
31-75	3.0%
76-125	2.5%
126-200*	2.0%
201-300*	1.5%
301+*	1.0%

* The Social Discount Rate from year 126 onwards stem from the Green Book 2011 (HM Treasury, 2011), as these longer time periods are not available any more in the newest version (HM Treasury, 2018).
Source: (HM Treasury, 2011); (HM Treasury, 2018)

5.1.4 Comparison

Figure 15 compares the different discounting schemes and provides some examples used in the literature and damage models. Note that the Ramsey Equation already implies a declining discount rate (the specific models are presented in Section 11). The reason for this is that they assume that g (pro memoria: the annual growth rate of per capita consumption) declines with time.

Figure 15: Comparison of discount rates implied by different sources



Source: own illustration, Infras. Data: UK Green Book 2011 and 2018 (HM Treasury, 2011, 2018). Damage models discount rates use the growth rate according to their Mimi-Versions (see Section 12). For FUND and PAGE, the regional growth rates have been aggregated weighted by current GDP. Note that the spike for PAGE around the year 2030 is due to a temporary increase in the model's projection of GDP.

5.2 Equity weighting: aggregation across space

5.2.1 Overview

The analysis of climate damages concerns groups with different income levels and thus faces the problem of how to aggregate them appropriately (see also e.g. Anthoff et al., 2009or Watkiss, 2011). This issue arises for all regionalized damage models.[58] Based on regional climate impacts and regional income levels, they monetarize regional damages and subsequently aggregate them to obtain global damages or the SCC.

The most straightforward aggregation option is to sum up the regional damages using market exchange rates. This approach has for example been used in Table 6.6 of the IPCC's second assessment report, working group III (Cooper et al., 1996 chapter 6). Using this approach, the poor regions' impact on global damages or SCC is low, because damages are often related to GDP either directly (e.g. expressed as percentage of GDP) or indirectly (via the value of a statistical life, which in turn is related to GDP).

Cooper et al., 1996 already noted that it is possible to use Purchasing Power Parity (PPP)-corrected GDP, which results in a lower discrepancy between richer and poorer countries and therefore gives damages in poorer countries more weight.[59]

To properly and stringently account for regional inequality Cooper et al., 1996, and others[60] argue that so called *equity weighting* should be introduced. Equity weighting can be derived from the aversion against inequality between regions, analogous to the aversion against inequality between generations in the context of discounting (see Section 5). Using the framework of a SWF as introduced above, those aversions are essentially hard linked into damage models. Consequently, equity weighting is an inevitable part of any regionalized model, be it explicitly or implicitly.

Discounting and equity weighting have a strong conceptual overlap. For the sake of clarity, in the following subsections we start discussing equity weighting in a static setting (damages in one time period), such that discounting plays no role. This allows us to focus on the features of equity weighting. In the last subsection, we return to a dynamic setting with several time periods where both discounting and equity weighting are relevant and show the derivation of SCC with equity weighting.

In its essence, equity-weighted global damages D_{global}^{EW} for a single time period are defined as:

$$D_{global}^{EW} = \sum_{i=1}^{n} w_i D_i,$$

where D_i are the regional damages (in €, using market exchange rates or PPP-corrected values[61]), w_i are the equity weights for region i and n is the number of regions. Setting all weights to unity implies no equity weighting.

[58] Note the damage models that do not have regions do not explicitly face this issue but nevertheless should in some way account for the effect of regional inequality.

[59] However, PPP adjustments are strongly dependent on the index used (PP, CP, COLI, Income) as well as on the chosen base year.

[60] For example Anthoff et al., 2009 and Fankhauser et al., 1997.

[61] If PPP-corrected values are used the influence of equity weighting decreases.

5.2.2 Illustrative example

Let us start with illustrating the impacts of equity weights. A common way to calculate equity weights is $w_i = \left(\frac{\bar{C}}{C_i}\right)^{\eta}$.[62] $\bar{C}$ is the global average consumption level, C_i is the regional consumption level, and η is the inequality aversion. A higher η results in higher weights for poorer regions.[63] Table 11 depict a fictitious world with four regions and a global consumption of 400€.

Table 11: Illustration equity weighting

	Consumption distribution [€]			
	CD 1	CD 2	CD 3	CD 4
Region A	100	50	30	10
Region B	100	80	70	30
Region C	100	120	120	100
Region D	100	150	180	260
η	**Equity-weighted global damages [€]**			
0	20.0	20.0	20	20
0.5	20.0	19.6	19.1	17.4
1	20.0	20.0	20.0	20
1.5	20.0	21.3	23.4	33

Fictitious example where each region has damages of 5% of its consumption level.

In each region, climate damages are 5 percent of regional consumption such that global damages without equity considerations are 20€. There are four different consumption distributions among regions, labelled CD1 to CD4. If there is no inequality (CD1), equity-weighted global damages are always 20€ (inequality aversion has no influence). If there is inequality (CD2 to CD4), equity-weighted global damages depend on the choice of η as follows:

- For η=0, there is no equity weighting and thus global damages simply are 20€ (that is 5% of the global consumption) for all CDs.
- For η=1, each region contributes the same weighted damages, namely 5€, irrespective of its consumption level. Consequently, global damages are again 20€ for all CD. This does not hold in general, but only as long as the relative damages — as in the example — are the same.
- For η<1, equity-weighted global damages decrease with inequality (from CD1 to CD4). Table 12 shows why: The decrease of weights of richer countries and thus the corresponding decrease of equity-weighted regional damages is not compensated for by increasing weights of poorer countries.

[62] The underlying assumptions that lead to this formula and its derivation are discussed below and also in more detail in e.g. Fankhauser et al., 1997.

[63] If γ is very high, only the damages of the poorest region are relevant for global welfare. This corresponds to a Rawlsian framework, where the primary concern is to increase welfare in the poorest region.

- For η>1, equity-weighted global damages increase with inequality. The reason is the converse argument to the previous case.

Table 12 provides the details for CD4, based on the equation $D^{EW}_{global} = \sum_{i=1}^{n} w_i D_i$. In the poorest Region A, for example, unweighted damages (η=0) are 0.5€, which represents 2.5 percent of global damages. In contrast, if η=1.5, weighted damages are 15.8€, which is about half of the global value.

Table 12: Illustration equity weighting – Details for CD4

Area	CD4: Consumption level C_i	η=0 (no equity weighting)	η=0.5	η=1	η=1.5
	[€]	Weights [-]			
Region A	10	1.0	3.2	10.0	31.6
Region B	30	1.0	1.8	3.3	6.1
Region C	100	1.0	1.0	1.0	1.0
Region D	260	1.0	0.6	0.4	0.2
Global ∑	**400**				
Equity-weighted regional and global damages [€]					
Region A		0.5	1.6	5.0	15.8
Region B		1.5	2.7	5.0	9.1
Region C		5.0	5.0	5.0	5.0
Region D		13.0	8.1	5.0	3.1
Global ∑		**20.0**	**17.4**	**20.0**	**33.0**

Fictitious example where each region has damages of 5% of its consumption level.

5.2.3 Formal derivation of equity weights

More formally, equity weighting can be derived as follows: It is common to use the utilitarian framework, which states that society should seek to maximizing total utility, which in this case is the sum of regional welfare. Thus, $GWF = \sum_{i=1}^{n} RWF(C_i)$,[64] where GWF is the global welfare function and RWF is regional welfare (both in units of "utils"). The RWF in turn is a function of

[64] A more general approach it to define $GWF = \frac{1}{1-\gamma}\sum_{i=1}^{n} RWF(C_i)^{1-\gamma}$. The parameter γ is the inequality aversion with respect to *utility levels* among regions. It is related to the introduced parameter η, which is the inequality aversion with respect to *consumption levels*. The two parameters may differ. Yet, the derivation in the main text implicitly assumes that both impacts may be subsumed using η. For a further discussion see e.g. Fankhauser et al., 1997. From this more general GWF, the utilitarian framework presented in the main text leads to setting γ=0, such that inequality in regional welfare levels does not matter and can simply be summed up.

the regional consumption level C_i (in €). Equity weights can be derived as $w_i = \frac{RWF_i'(C_i)}{RWF'(C_{Rep})}$.[65] This leads to the following formula for equity-weighted global damages:

$$D_{global}^{EW} = \frac{1}{RWF'(C_{Rep})} \sum_{i=1}^{n} RWF'(C_i) * D_i$$

$RWF'(C_i)$ is the change of regional welfare for a marginal change of regional consumption C_i (unit is "utils/€"). This translates regional damages D_i into regional welfare loss. Those regional welfare losses are summed up over all regions n. Finally, the first term converts this aggregated welfare loss back into monetary terms (the so-called normalization). To do so, a representative consumption level C_{Rep} has to be chosen. This choice has a huge influence on the value of equity-weighted global damages. If a poor country with a low consumption level is chosen, $RWF'(C_{Rep})$ is large (i.e. the additional benefit of consumption is high) and the normalization leads to smaller weighted global damages and vice versa. According to Anthoff et al., 2009, Table 4 the region chosen for normalization can lead to differences of the SCC of up to a factor 20. Normalization to a certain region means that damages around the globe are accounted as if they would all accrue within that specific region.

Note that different normalization choices do not amount to different optimal emission paths in a CB-IAM or — more generally speaking — change the cost–benefit analysis in a utilitarian framework. Yet, they make a huge difference if results (total damages or SCC) are presented and subsequently used in other contexts (e.g. when compared with abatement costs of other studies that use a different model set-up). Therefore, preferably all costs and benefits should be calculated within the same model framework. If this is not possible, the normalization ought to be done with respect to the region where the results are subsequently used.

Box 7: Justification for or against equity weighting

Fankhauser et al., 1997 provide several justifications for not using equity weighting:

1. Equity adjustments are not applied in other policy areas

2. The current income distribution is either assumed to be just or distributional issues do not matter at all (i.e. there is no inequality aversion).

3. There are lump sum transfers from richer regions (with more emissions) to poorer regions to compensate climate damages

4. Distributional issues among regions should not be mixed with climate policy. Distributional issues should thus be dealt with specially targeted instruments and not implicitly with climate policy (i.e. climate policy should not be made more stringent because of inequality among regions).

The first three points are either morally not justifiable (points one and two) or currently unlikely (point three). We assume that it is mainly because of the fourth point that equity weighting is often not used (e.g. it is not used in the US (IAWG, 2016) and not even discussed in the accompanying report (National Academies of Sciences, Engineering, and Medicine,

[65] $w_i = \left(\frac{\bar{C}}{C_i}\right)^{\eta}$ of the illustrative example then follows from this, using (1) the common iso-elastic form $RWF(C_i) = \frac{C_i^{1-\eta}}{1-\eta}$ and (2) normalizing with respect to the marginal utility of consumption assuming that global consumption would be equally distributed among regions.

2017). Yet, Stiglitz and Stern argue that "the social cost of carbon may have to be adjusted upward, if the implementation of policies to reduce those inequalities is not feasible" (Stiglitz et al., 2017, p. 52).

5.3 Aggregation across time and space

In a damage model, Ramsey-type discounting (if applied) and equity weighting act simultaneously and their effects interact. In order to account for both, the SCC are calculated as follows.

$$SCC_{present}(ET) = \frac{1}{RWF'(t=0, C_{Rep})} \sum_{t=ET}^{FTP} \sum_{i=1}^{n} (1+\delta)^{-t} * RWF'(t, C_i) * D_i(t, ET)$$

Going from the right to the left, this equation does the following: $D_i(t, ET)$ are the damages in region i at time t due to the emission of an additional ton of CO_2 at time ET<t (ET=emission time). Damages are multiplied with the marginal change in regional welfare at time t (at the consumption level of the region i at that time). This step includes both the equity weighing (see Section 5.2) as well as the growth discounting part of the social discount rate (see Section 5), as consumption levels differ between regions and time periods. Next, the welfare change in region i at time t is discounted to the present[66], using the pure rate of time preference δ (this is the time discounting part of the Ramsey Equation). The discounted welfare changes are subsequently summed over regions and time periods (from emission time ET until the final time period FTP considered in the model). Finally, this sum is normalized using the marginal welfare of the representative region at time t=0.[67]

Box 8: The multiple roles of the elasticity of the marginal utility of consumption

Equity weighting is based on regional inequality aversion, whereas growth discounting (see Section 5.1.2) is based on intertemporal inequality aversion. In damage models both aversions are usually modelled using the same parameter, namely the elasticity of the marginal welfare of consumption (η). In addition, this parameter is also used as risk aversion (see Section 3.1.2.2). Thus, in current models an increase in η may have various impacts on SCC:

► A higher regional inequality aversion increases SCC if the reference region is richer than the global average (and decreases SCC if the reference region is poorer than the average).[68]

► A higher intertemporal inequality aversion decreases the SCC as the social discount rate increases.

► A higher risk aversion increases the SCC.

Note that these various effects could also be disentangled using separate parameters (e.g. Anthoff & Emmerling, 2016 disentangled the first two in FUND and RICE).

[66] Note that $SCC_{present}$ (ET) refers to the damages from today's perspective (t=0) of emission that occur later (ET>t). It is also possible to determine $SCC_{current}$ (ET) which would be the SCC of an emission at the same time (ET>t) but seen from ET's perspective. In the latter case the discounting term in the equation would read $(1+\delta)^{-(t-ET)}$.

[67] Another option is to use t=ET.

[68] Under the common assumption that the future will be richer than the present.

6 Climate model

The climate system model's outputs (in particular, the temperature increase) serve as inputs to the damage function. The climate module has thus a major influence on the SCC and damage models differ considerably in this respect. See e.g. Warren et al., 2010, which compare temperature responses of different climate models for identical emission scenarios, or Figure 26, which compares outcomes from AR5 and the damage model DICE. In the following we explain how this discrepancy arises. Explicitly or implicitly, damage models consider two components of the earth system:

- a carbon cycle model which translates anthropogenic CO_2 emissions into an increase of the atmospheric CO_2 concentration,
- a climate system model which investigates the changes in the climate system (temperature, precipitation, sea-level rise, etc.) due to the elevated CO_2 concentration (and other GHG) in the atmosphere.

In the following we provide an overview of these two components.[69] Details on how these effects are represented in specific models are deferred to Section 11. Note that even though CO_2 is not the only GHG, it is the most important one and thus the focus of the section.[70] Other GHG and their social costs will be discussed briefly in Section 9.1.

6.1 Carbon cycle

The main reservoirs of CO_2 — or more precisely the carbon embodied in it — are the solid earth, the deep ocean (≈ 37′100 GtC), the biosphere (≈ 2′300 GtC) the surface ocean (≈ 900 GtC), and finally, the atmosphere (≈600 GtC) (Menon et al., 2007).[71] Due to physical, chemical or biological processes, carbon moves naturally between these reservoirs. This natural carbon cycle is very complex and works on different timescales. The ocean is generally divided into a well-mixed surface zone (50-100m) and the deep ocean beneath it. The deep ocean contains vast amounts of carbon, yet it is rather inert (turnover time of several centuries.). The deep ocean plays thus a decisive role for the carbon cycle in the long run only. The surface ocean, the biosphere and the atmosphere on the other hand are in direct contact with each other and exchange carbon on timescales of seconds to years.

The carbon cycle has to be modelled correctly, as the atmospheric CO_2 concentrations are the basis of all further impact calculations. If e.g. a model predicts that emitted CO_2 leaves the atmosphere too soon or in too large amounts, the SCC-estimate would be too low.

First, models have to calculate which fraction of anthropogenic CO_2 emissions remains in the atmosphere (and causes climate change).[72] This atmospheric fraction depends on the distribution between the fast-mixing reservoirs and may change with advancing climate change.

[69] This section draws on (Oberpriller, 2013).

[70] This focus in in line with the literature's focus, which is partly for historical reasons, as CO_2 is the most prominent and thus most discussed GHG. Non-CO_2 GHGs such as methane or nitrous oxide currently only contribute about half as much to the global warming effect compared to CO_2. In addition, the effect of non-CO_2 GHGs is partly balanced by the cooling effect of aerosols (Forster et al., 2007)

[71] The solid earth (which mainly consists of rocks) is by far the biggest reservoir. Yet, it interacts so slowly with the other reservoirs (on timescales of 10'000 years and more) that it does not play a role on human timescales. It may thus be neglected.

[72] Anthropogenic CO_2-emissions are those emissions additionally caused by humans (burning of fossil fuels, land-use change, geogenic emissions from cement production, etc.). Those contrast with emissions from the natural carbon cycle, where sources and sinks are balanced on a decadal scale.

Furthermore, anthropogenic CO_2 that enters the oceans increases its acidity. Because of the ocean chemistry, a more acid ocean can take up less CO_2 emissions. Thus, due to this well-understood chemical effect alone, the atmospheric fraction increases with the accumulated anthropogenic CO_2 emitted since preindustrial times.

Second, since the last ice age, atmospheric carbon sinks and sources have been roughly in balance on timescales larger than a decade and thus the atmosphere's natural carbon concentration remained stable. Yet, climate change may interfere with this balance. Even small changes in the natural carbon cycle due to climate change have the potential to affect the atmosphere's CO_2 concentration significantly. This is because the atmosphere is at the centre of the natural carbon cycle, yet it has the smallest reservoir size.[73] However, knowledge of this so-called carbon cycle feedback is only fragmentary and thus difficult to include in models. A related topic whose discussion goes beyond this report's scope, is the notion of so-called tipping points associated with the natural carbon cycle and the climate system at large (Lenton et al., 2008).[74]

The instantaneous airborne fraction of anthropogenic CO_2 has in the past been approximately 45%, the remainder was taken up by the ocean (24%) and land (31%). Around 30% of this airborne fraction will remain in the atmosphere for at least several thousand years (Archer et al., 2009). As discussed above, these numbers may change and strongly depend on the total amount of CO_2 emitted and on the impacts of climate change.

6.2 Climate system

A commonly-used metric of CO_2's potential to change the climate is the "equilibrium climate sensitivity" (ECS). It is the long-term increase in global mean temperature[75] if the CO_2-concentration is first doubled as compared to the pre-industrial level and then kept constant.

In 1979, (Charney et al., 1979) have been the first to roughly estimate the ECS to be within a range of 1.5 – 4.5°C, with a best guess of 3°C. Since then, there has been intense research on this topic. A multitude of feedbacks in the climate system on various time-scales have been identified whose influence on the ECS is notoriously difficult to predict (Roe & Baker, 2007; (Bony et al., 2006)).[76] Thus, despite a much better understanding of the climate system, it was not possible to decrease the uncertainty range since 1979. On the contrary, since scientists recently became aware of feedbacks that may be strongly non-linear (e.g. related to the natural carbon cycle; see "tipping points" above). Although these remain speculative, a climate sensitivity that is well

[73] During the ice ages, for example, the atmosphere contained about one-third less carbon, triggered only by small changes of the earth's orbit around the sun.

[74] For example, accelerated dieback (due to precipitation changes and extreme heat) or enhancement (due to CO_2-Fertilisation and warming) of the biosphere or sudden extensive methane emissions due to thawing permafrost.

[75] Note that temperature increases are more pronounced over land than over the ocean, as the latter take longer to warm up. Thus, countries' temperature increases are higher than global averages seem to suggest (most notably in the polar regions and for high altitude regions).

[76] At short to medium timescales the most important climate feedbacks are, the Cloud Feedback (probably increases ECS), Surface Albedo Feedback (increases ECS), the Water Vapor Feedback (increases ECS), and the Lapse Rate Feedback (probably decreases TCS). Most uncertain is the Cloud Feedback, which occurs since climate change alters cloud patterns, which influences both incoming solar radiation and outgoing long-wave radiation. The Surface Albedo Feedback occurs since climate change leads to increased melting of bright snow and ice, which are replaced by darker land or ocean. Thus, less incoming solar radiation is reflected to space and instead absorbed. The Water Vapor Feedback and the Lapse Rate Feedback are strongly connected. Climate change heats the atmosphere, increasing the water vapor content, which by itself is a greenhouse gas further strengthening the greenhouse effect. At the same time, the increase in water vapor leads to a stronger warming in the upper parts of the atmosphere as compared to the lower parts. Consequently, the lapse rate (which is the temperature decrease with height) is reduced which — roughly speaking — strengthens the earth system ability to radiate heat towards space and thus weakens the greenhouse effect. The two effects partly cancel each other and are thus often presented as a net effect. For a more detailed discussion, see Bony et al. (2006). For long-term earth system feedbacks (e.g. ice-sheets or vegetation) see (Knutti et al., 2017) and references therein.

above 4.5°C cannot be ruled out (especially over longer timescales when long-term feedbacks kick in[77]) and there is no agreed-upon upper boundary (Knutti & Hegerl, 2008).

Because the oceans warm slowly, it also takes several decades or even centuries to fully reach the long-run equilibrium (Roe & Bauman, 2013). As it is not likely that the atmospheric composition remains constant over such long periods (due to natural and human influences), the equilibrium may never be reached. It is thus also important to complement the ECS with an appropriate climate response-time (which is included in climate modules of damage cost models). Given these problems, the focus has recently shifted to other metrics to substitute the ECS (Knutti et al., 2017).

One such metric is the *transient climate response* (TCR). It assumes that CO_2-concentration is increased by 1% per year. TCR then is the temperature increase after 70 years, i.e. when concentration has doubled. ECS and TCR are correlated. Nevertheless, there is a much stronger consensus about the value of the TCR, as it can be derived from the observable warming more directly and the complex long-term feedbacks are of minor importance. Compared to ECS, TCR is arguably a better metric in this context, as it is more related to policy-relevant time horizons (Frame et al., 2006) and does not focus on a hypothetical long-run equilibrium. PAGE uses the TCR in its climate module.

The newest concept is the so-called *transient climate response to cumulative carbon emissions* (TCRE). It builds on the fact that GCMs found an approximately linear relationship between the global mean temperature change and accumulated emissions at a certain point in time. The IPCC estimated the TCRE to be likely (i.e. with a probability of 66 percent) in the range of 0.8 – 2.5°C / 1’000GtC (Knutti et al., 2017). The TCRE is a useful metric, as it is simple to use and allows to directly determine the remaining carbon budget if a certain temperature target ought to be met. It is thus highly relevant to policy design (see further e.g. MacDougall 2017 and references therein).

While the global average temperature change is a simple and good indicator for climate change, it can also be misleading. The actual damages in a specific country depend on local changes in a variety of climatic factors, including temperature but also precipitation, extreme events or changes in climate patterns and seasons. Furthermore, the more global predictions are scaled to a regional level, the higher the uncertainties.

Finally, climate change also leads to sea level rise and ocean acidification. Sea level rises because water expands when it gets warmer and because of melting glaciers and ice sheets. While the former is comparatively easy to calculate (for a given temperature increase), the latter is extremely complex, as the dynamics of ice sheets are not well understood(Rahmstorf, 2010). In addition, the respond time is slower than for temperature change; but the exact timescale involved is a matter of intense debate: It is likely that sea-level rise continues even if the temperature has stabilized, due to so-called threshold effects.

Ocean acidification occurs as the CO_2 that is taken up by the ocean dissolves and forms carbonic acid. This has impacts on marine live and the food chain (e.g. the possibility of certain organisms to build shells deteriorates as the surrounding water turns more acidic). While all models consider sea-level rise (albeit some, e.g. DICE, only implicitly), ocean acidification is considered by none of them.

[77] For that reason, the literature introduced the earth system sensitivity (ESS), which includes the effects of long-term earth system feedback loops, such as changes in ice sheets or changes in the distribution of vegetative cover. The ECS does not include those effects. However, these distinctions are sometimes fuzzy.

7 Damage function

Damage models translate climate change impacts into monetary damages using damage functions. How this is done strongly influences the result of a model. Yet, there is no reliable and commonly agreed-upon way to define and calibrate damage functions and there exists a large body of literature on the implications, differences and shortcomings of damage functions (see for example Stanton et al., 2009, Tol, 2009(and its correction and update (Tol, 2014)); Stern, 2013, Table SM10-1 in the supplementary material of AR5, WGII, chapter 10 (Arent et al., 2014); Van den Bergh & Botzen, 2015, Pindyck, 2017, Howard & Sterner, 2017, Nordhaus & Moffat, 2017,, Tol, 2018, or Estrada et al., 2019). These publications reveal a lively debate concerning the methods used (e.g. biases in data selection or handling of high-temperature estimates). In the following, we provide a structured overview of the main arguments.

7.1 Damage impact categories

Climate change impacts a variety of sectors and these impacts differ regionally. For certain impacts, the causal connection to climate change is obvious (e.g. droughts, storms or sea level rise). In addition, there are political or economic impacts where non-climate-related factors play an important role and climate change is merely an aggravating factor (e.g. political instability, migration). For those impacts, causal links are indirect and thus more complex (Peter et al., 2020).

In most sectors, climate impacts cause damages. Yet, there are also sectors where climate change is beneficial (e.g. less heating demand, shorter shipping lines across the poles, CO_2-fertilitation in agriculture). While damage models strive to monetize these impacts on a regional scale as realistically as possible, they remain limited in several ways. To illustrate the challenge of this task, Table 13 provides an extensive but arguably still incomplete overview of relevant categories (categories partly bundle related sectors).

Table 13: Damage impact categories

Categories of climate impacts	Likely Impact on Damage Costs
Direct impacts	
Agriculture and forestry	Increase or Decrease
Coastal zones	
Water resources	Increase
Human health	Increase
Increase in the intensity and / or frequency of extreme weather events (e.g. hurricanes, storms, floods, droughts, storm surges from seas/oceans)	Increase
Sea level rise	Increase
Ocean acidification	Increase
Desertification	Increase
Changing patterns of precipitation and temperature (e.g. Indian Monsoon)	Probably Increase
Collapse of forests and biodiversity loss (e.g. Amazonian Rainforests)	Increase

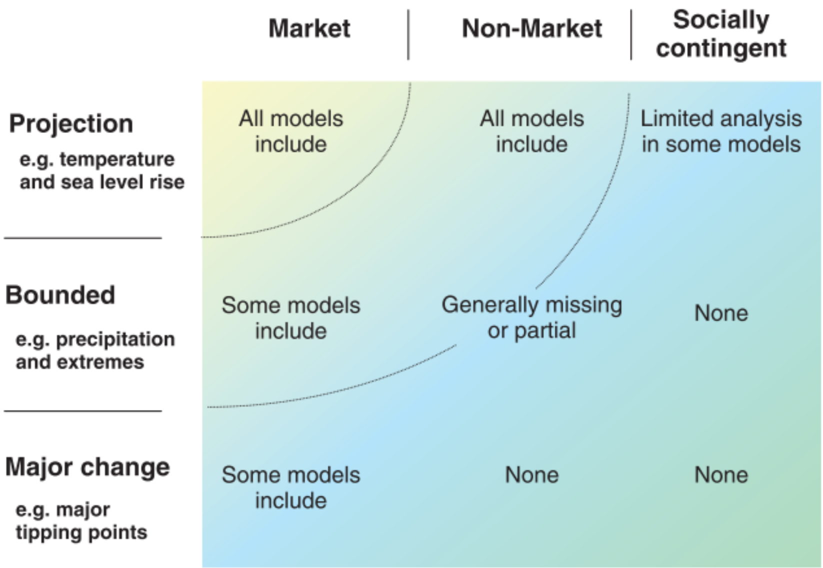
Tipping points / catastrophic climate change (e.g. collapse of land-based polar ice sheets or release of sea-bed methane, collapse of the oceanic thermohaline circulation, collapse of tropical forests)	Increase
Chaotic and unstable behaviour of complex ecosystems	Probably Increase
Indirect political or economic impacts	
Adaptation cost	Net Decrease (if done optimally)
Political instability and violent conflicts (e.g. conflicts in Darfur related to dried out pastures)	Increase
Large migration flows (e.g. desertification in and around the Sahara or relocation of populations on islands and coastal areas due to rising sea levels)	Increase
General equilibrium effects (e.g. disruptions in the supply chains of globalized production and trade)	Increase and Decrease
Energy consumption (more cooling, less heating)	Net effect unclear
Generation of (renewable) energy	Unclear
Shipping lines at the poles	Decrease

Source: Categories based on van den Bergh & Botzen, 2014.

Figure 16 provides another view on the extent to which damage models cover important aspects of climate change. While market impact connected to projections are included in models, other impacts are missing. This is especially true for major changes connected with non-market and socially contingent impacts.[78].

[78] Watkiss, 2011, p. 360 provides the following explanation for the figure: "On the horizontal axis, the matrix included three categories of effect: market, nonmarket, and socially contingent effects, the latter associated with large-scale dynamics related to human values and equity that are poorly represented in cost values, e.g., conflict, famine, and poverty On the vertical axis were three categories of climate change. First, effects that could be relatively well projected (at least in sign) such as average temperature and sea level rise; second, more uncertain parameters with more complex bounded ranges such as precipitation and extreme events; and finally, major catastrophic events, discontinuities, or tipping points/elements, such as the instability of the West Antarctic ice sheet, which could exhibit threshold type behavior at a critical point but where thresholds and subsequent effects are highly uncertain."

Figure 16: Coverage of categories in damage models



Source: (Watkiss, 2011)

In order to provide a more comprehensive framework for climate impacts beyond economic damages alone, the IPCC has put forward the so-called five 'Reasons for Concern' (O'Neill, Oppenheimer, et al., 2017):

- Risks to unique and threatened systems
- Risks associated with extreme weather events
- Risks associated with the distribution of impacts
- Risks associated with global aggregate impacts
- Risks associated with large-scale singular events

7.2 Types of damage functions and calibration

Damage functions seek to translate these various impacts into monetized damages. There are essentially three types of damage functions used in the literature: (1) Aggregate and highly stylized functions, (2) sector-specific enumeration of impacts (3) macroeconometric estimates. We will discuss the first two types in the following. The third type is discussed separately in Section 7.7.

One approach is to use **aggregate and highly stylized functions** of the change in global mean temperature (e.g. DICE or PAGE use such kind of damage functions).[79] These aggregate functions are power functions ($Damages = a * \Delta T^b$) with the exponent b greater than one.[80] They are loosely based on more sectoral disaggregated damage estimates in relevant sectors[81], such as

[79] Apart from the temperature change ΔT, models use other inputs to the damage function such as sea-level rise (e.g. FUND, PAGE and DICE-versions prior to 2013R) or the *rate* with which the climate changes (e.g. a part of the agricultural sector in FUND). The higher this rate, the higher are the damages, under the assumption that higher rates make adaptation more difficult. Other parameters, such as precipitation changes, are not used as inputs.

[80] b>1 corresponds to the assumption that incremental damages for the same temperature change are more severe for higher temperature levels.

[81] "Sectors" is used here in a broad sense as areas/scopes/zones/etc affected by climate change.

agriculture, sea level rise, health, work productivity and in some cases non-market damage and catastrophic damages. In that sense, the function does include those sectoral disaggregated impacts (as done e.g. in DICE (W. Nordhaus & Sztorc, 2013)). There is, however, no underlying economic theory that can be used to derive the specification of aggregate damage functions. The power form is essentially chosen arbitrarily, primarily for its simplicity. In addition, there exists no primary data against which to calibrate aggregate damage functions. According toPindyck, 2013, the usual approach is to select values such that damages for a temperature increase of 2°C are 1% –2% of GDP, while for an increase of 3°C or 4°C they are 2% – 4% of GDP. Especially for high temperatures however, no data exists and calibration exercises may be very sensitive on these data points(Howard & Sterner, 2017).

Another approach is to enumerate damages for several sectors using **sector-specific damage functions**. This approach has been pioneered by FUND, which includes 14 damage sectors[82] (see further Section 12.2). Sector-specific damage functions try to base damage estimates on underlying physical process models (e.g. impact on crops) or structural economic models (e.g. impact on cooling demand) (National Academies of Sciences, Engineering, and Medicine, 2017). The problem is, however, that data for calibration is scarce. It is currently only available for some regions of the world (e.g. the US; see Arent et al., 2014), whereas for developing countries, where climate change impacts are projected to be large, data is generally of low quality. Data for high temperature impacts is very scarce too. In addition, the data refers mostly to market damage, as monetization of non-market impacts is difficult. The sectoral damage functions of FUND are further still based on the assessment of the impact literature conducted in the late 1990 with only minor updates in the early 2000 (see table 5-2 in National Academies of Sciences, Engineering, and Medicine, 2017), even though data for updates for modest temperature increases may now be available (see table 5-3 ibidem).

Cross-sectional analysis is sometimes used to estimate sector-specific damage functions. The basic idea is to compare two different geographical locations which are as similar as possible except for their average temperature. The warmer place accordingly serves as estimate of damage costs for the colder place if impacts of climate change manifest themselves. The key challenge is to account for the fact that households, agriculture, industry, culture, etc. of the warmer place are adapted to the prevailing climate, such that this approach implicitly assumes a "complete" adaptation of the currently colder place. For a further discussion of these methods, see Section 7.7 and Appendix C.

7.3 Non-market impacts and substitutability

Some impacts can be monetized based on market prices (e.g. loss of agricultural yields, increase in electricity demand due to more air conditioning, or inundated land). For non-market impacts, there are no markets to observe prices directly (e.g. human health or death, political stability, biodiversity, or loss of local communities). A single impact may also have market and non-market components, such as a hurricane that destroys properties (market) and leads to loss of life (non-market). Non-market impacts thus have to be monetized, which introduces uncertainties and requires that the underlying assumptions be made transparent(National Academies of Sciences, Engineering, and Medicine, 2017).[83]

Different valuation methods exist to derive monetary values for non-market impacts. For example, the people's willingness-to-pay to avoid environmental deterioration or the

[82] Note that several sectors in the FUND model relate to a single category. There are, for example, four sectors related to health.

[83] The prediction of the impact is not necessarily more difficult for non-market impacts. It is for example virtually certain that coral reefs will disappear if climate change reaches 2°C. Yet, it is unclear how we can monetize the loss of coral reefs.

willingness-to-accept compensation for a given deterioration. Nevertheless, existing studies are not sufficient to cover the manifold non-market effects in a deep sectoral and regional differentiation. When evaluating damages related to human health, usually either the loss of life in years or a deterioration of the quality of life (also expressed in years) are calculated. These are then monetized using the so-called statistical value of life or the value of a year of morbidity. Both values and their regional differentiation are subject to ethical controversies.

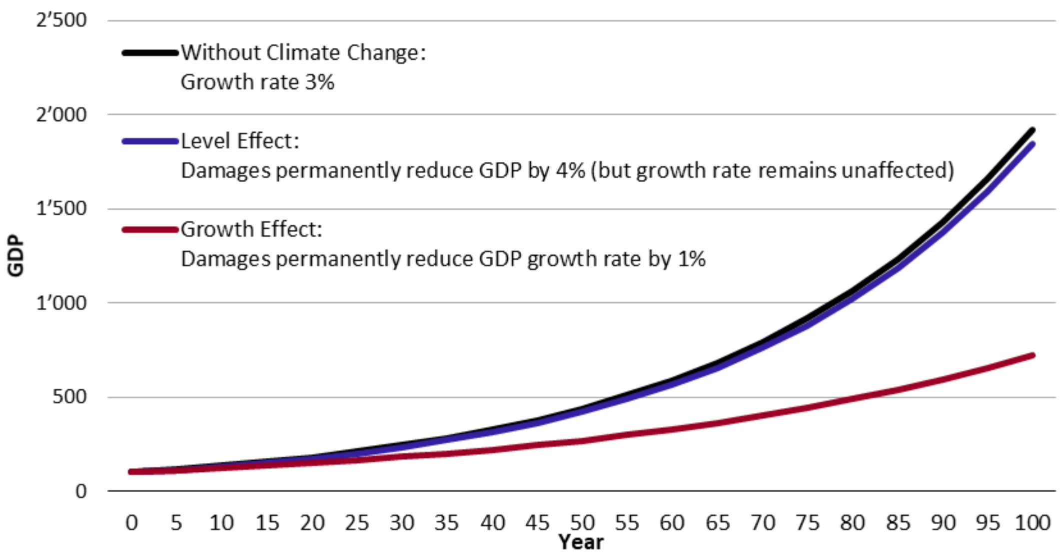
Damage models usually sum all positive and negative aspects during aggregation, such that the overall cost is the net of all market and non-market damages (and benefits). This implies full substitution between different impact categories. This is a strong assumption and it is unclear whether such a high degree of assumed substitutability is acceptable. The concept of strong *sustainability* would not allow for such an aggregation at all, as it postulates that substitution is not possible. Under the concept of weak sustainability, aggregation is possible. It uses a certain elasticity of substitution, which is roughly speaking a crude measure of the exchange rate with which a decrease in natural capital can be offset by an increase in other forms of capital (physical, intellectual and human) (see e.g. Heal, 2017; Watkiss, 2011).

In addition, damage models usually assume that the value (or the elasticity of substitution) people attach to ecosystems remains constant. Yet, if a service becomes scarcer in the future, its value most likely increases (e.g. freshwater in dry regions). Because most ecosystems degrade with climate change, monetized damages of ecosystem damage may rise faster when taking increasing scarcity into account(Drupp & Hänsel, 2018; Gollier, 2010; Revesz et al., 2014)..

7.4 Impacts on GDP *growth rate* vs. GDP *level*

The damages of climate change are usually modelled in relation to GDP. There are two different approaches. Damages may reduce the *growth rate* or the *level* of GDP. This is a very influential assumption as growth-rate effects accumulate with time, whereas level effects do not (see Figure 17).

Figure 17: Illustration of impacts on GDP of changes of growth rate vs. level



Source: own illustration, Infras.

The standard versions of DICE, FUND and PAGE use the level approach. They set an exogenous growth rate to determine the baseline GDP (see also Figure 43).[84] Current damages are expressed as a percentage share of the current baseline GDP. The underlying assumption is that while damages reduce current output (and thus income, consumption, and investment), the capital stock of an economy — and thus its ability to grow — remains unchanged.

This assumption has been contested (see e.g. Pindyck, 2013; Stern, 2013). Damages to infrastructure, health, human settlements, or natural ecosystems, for example, reduce the capital stock. Damage models that calculate damages solely as a share of GDP thus neglect that climate change undermines the drivers of economic growth and consequently the growth rate itself. If climate change is modelled to affect the growth rate, the SCC increases for two reasons. Due to the compounding effect of a lower growth rate, the gap (i.e. the damage) between the GDP level with and without climate change will increase over time (see above). Second, slower economic growth decreases the growth discounting component of the Ramsey Equations (see Section 5.1.2).

For that reason, Stern, 2013, p. 849, among others, argues that "exogenous growth of any long-term strength is simply not credible in the face of the scale of the disruption that could arise at these higher temperatures. Potentially large-scale destruction of capital and infrastructure, mass migration, conflict, and so on, can hardly be seen as a context for stable and exogenously growing production conditions" and mentions four reasons why the growth rate might be affected by climate change:

- Climate change could undermine the key drivers of endogenous growth (e.g. if investment is mostly used for repairments and replacement, it may induce much less learning than investment that involves innovation and new ideas).
- The knowledge, structures, networks, and relationships that organizational or social capital represent, could be disrupted or destroyed by hostile climate and extreme events, as well as by migration and conflict.
- Climate change results in a (permanent) reduction of capital (e.g. destroyed infrastructure)
- Even if capital stocks are not destroyed, the ability to use them effectively might be damaged by a hostile environment.

In addition to these purely theoretical arguments, the rate vs. level question is also subject of discussions in the macroeconometric literature:

Dell et al., 2012 used panel data of 125 countries and a timespan of 20 years to estimate a dynamic growth model that considers level and growth effects of weather shocks. The authors claim that the level effect tends to reverse itself once the weather goes back to normal (as in the case of agricultural yields), while the growth effect has a lasting effect (as in the case of, e.g., derailed innovation). Dell et al., 2012 results show that only in poorer countries do higher temperatures have a large, negative effect on economic growth (growth is reduced by approximately 1.3 percentage points for every degree increase in temperature). In rich countries on the other hand, the results are not robust. They find little evidence of a level effect, such that the impact of weather shocks is predominately in the medium run. The per-capita reduction is

[84] GDP growth is entirely exogenous in FUND and PAGE. DICE is a neoclassical growth model where climate change may alter economic growth indirectly through capital stock reductions.

approximately 8.5 percent for every degree warmer from the cross-sectional analysis estimating medium-run effects.

Burke et al., 2015 find that long-run growth rates could be affected by temperature changes. They use panel data of 166 countries over the years 1960-2010. They presuppose a non-linear relationship between country-specific deviations to growth trends and country-specific deviations from temperature and precipitation trends after accounting for shocks common to all countries. That is, they presuppose a growth rate effect. Their results indeed show that overall economic productivity has a non-linear, concave relationship with temperature. Economic productivity is estimated to peak at 13°C, such that productivity of cold countries increases as temperature increases up to an optimum and vice versa. Both have a lasting effect on the growth rate (see also the example in Figure 19). The authors also do not see any evidence of a "catch-up" behaviour after a year of losses. They find that both rich and poor countries respond similarly to temperature, thereby arriving at the conclusion that poor, tropical countries incur larger impacts because they are, on average, hotter and not because they are poor. For a further discussion of this study see also Section 7.7.2. Kalkuhl & Wenz, 2020 do not find evidence of an impact on the growth rate. They find, however, evidence that a one-time temperature increase strongly affects output levels. This finding thus differs from Burke et al. (2015). Kalkuhl & Wenz, 2020 claim that this is due to the choice of the regression model

Thus, despite intense research, the answers to the growth-vs.-level question remain inconclusive. For a more detailed discussion in the literature see also Burke et al., 2015; Dell et al., 2012 Chapter C.2; Dell et al. 2014 Chapter 4.2.3; Newell et al., 2018 Chapter 2 or Kalkuhl & Wenz, 2020.

Most likely, climate change will affect both GDP level and its growth-rate. Yet, a robust quantitative assessment of both effects is currently not available — and will likely not be available in the foreseeable future.

7.5 Uncertainty and catastrophic climate change

First attempts to model the economics of climate change disregarded uncertainty and used a deterministic approach (W. D. Nordhaus, 1977).Yet all aspects of climate change modelling are highly uncertain (the climate sensitivity, the choice of the considered impact sectors, the parameters, and the functional form of the damage function, etc.). That is why it is now common to consider uncertainty in damage models. Related to parametric uncertainty (see in Section 2.3.1) for which the probability density function is known (type "risk"; see Table 2) the following — not mutually exclusive — approaches are being used:

- Adjust the social discount rate (SDR): Either reduce the SDR or use a SDR that declines over time (for more details see Section 5.1.2.4). Both approaches lead to higher SCC.
- Present sensitivity analysis results for several combinations of parameter values. This is mostly done for parameters associated with normative uncertainty (e.g. the pure rate of time preference).
- Run a Monte Carlo simulation: attach probability distributions (mostly normal, triangular or uniform) to certain parameters and calculate SCC-values for thousands of random combinations. This results in an average value and an uncertainty range. The respective approach introduces new sorts of uncertainties (mean vs. median, handling of outliers, etc.). A further challenge for Monte Carlo simulations is to account for the correlations of

uncertain parameters (e.g. the value of the equilibrium climate sensitivity and the time until equilibrium is reached). Monte Carlo simulations are usually done for parameters associated with scientific uncertainty.

These approaches address only a part of the inherent uncertainty. Accounting for the other reasons of uncertainty (inclusion, structural) and severity of uncertainty (ambiguity, tipping points, or deep uncertainty) as listed in Section 2.3 is more difficult.

An approach to account for situations where the probability distribution is unknown (ambiguity; see Table 2) is the "smooth ambiguity model" (Klibanoff et al., 2005, 2009),which extends the expected utility theory by assuming that there is a set of underlying probability distributions to account for the problem that the probability distribution is itself uncertain. Applied to the context of climate change, this concept increases the SCC (Millner et al., 2010). In addition to risk aversion triggered by the uncertainty as given by a single probability distribution, there is also "ambiguity aversion" triggered by the uncertainty that even the probability distribution is unknown. Millner et al., 2013 and (Lemoine & Traeger, 2016) show that ambiguity aversion is not simply the same as increasing the risk aversion but can drive policy choices in different directions.

But even the smooth ambiguity model cannot account for the possible impact of *catastrophic* climate change: a very high climate sensitivity and/or very high damages caused by a moderate temperature increase. Those catastrophes are closely related to the concept of tipping points in the earth system (see Box 9). Mathematically, this situation is commonly modelled using probability distributions with "fat tails" or "tail risks": Compared to a normal distribution, distributions with fat tails have much larger probabilities associated with extreme outcomes.

Box 9: Tipping points in the climate system

A tipping point occurs when climate change crosses a specific threshold over a specific time span. Strongly nonlinear effects take place at certain elements of the earth system, which dominate the external forcing such that this element changes essentially irreversibly into a new state ("hysteresis"). An example is the Greenland ice sheet. Warming at the periphery lowers the altitude of the ice sheet. More melting takes place because temperatures are higher at lower altitudes. This causes a self-enhancing feedback loop which, at a certain point, cannot be reversed, even if global temperatures would decrease again.

There are several tipping points in the climate system, none of which can be predicted precisely (Lenton et al., 2008). Most tipping points are potentially harmful, such as the breakdown of the Atlantic meridional overturning circulation, accelerated surface heating through snow-albedo feedback, methane emissions from thawing permafrost, or the disappearance of the Amazonian Rainforest (irreversible change of the moisture recycling pattern). However, there are also examples of potentially beneficial tipping points, such as the strengthening of the West-African monsoon, which would lead to more rainfall in the Sahel/Sahara zone.

Note that tipping points play a special role in scenarios, which aim at a certain temperature threshold but allow for a temporary overshoot (overshoot-scenarios). A overshoot may be sufficient to reach a tipping point and trigger its corresponding runaway process if temperature drops thereafter.

If probability distributions have fat tails, the combination of uncertainty and risk aversion can outweigh all other influences: In a series of articles, Weitzman (Weitzman, 2009, 2014) states that because the climate sensitivity parameter has no agreed-upon upper bound risk aversion could theoretically imply that society is willing to spend an infinite amount to prevent climate change from happening ("dismal theorem"). Even though such an extreme result may be an artefact of the mathematical setting (W. D. Nordhaus, 2009), a part of the literature argues that the basic argument remains valid: Climate mitigation shall be primarily seen as an "insurance" against catastrophic climate change (Pindyck, 2013a, 2013b, 2017). Consequentially, the possibility of a catastrophic outcome would be an essential driver of the SCC as compared to more probable events. This is currently not the case in DICE and FUND, which use gradual and continuous damage functions. PAGE considers catastrophic outcome since the 2002 version. There is a certain chance of a large-scale discontinuity (chance of 1–20% that GDP drops by 5–20%) above a certain temperature threshold (2–8°C). That is, damages increase very sharply when temperature reaches that threshold. However, because of climate change's deep uncertainty, the threshold and the extent of the incurring additional damages in case it is crossed have to be chosen arbitrarily by the modellers.[85]

7.6 Adaptation

Local adaptation measures reduce the impacts of climate change and thus have a large influence on the damage function. There are many climate-sensitive sectors, each of which has specific adaptation possibilities, costs, and benefits. The extent and success of adaptation also depends on the vulnerabilities and capabilities of regions and societies. Consider the example of the Netherlands and Bangladesh: Both will be highly affected by sea-level rise, but the Netherlands are better able to handle the negative consequences, as the country is richer and has a long tradition of building protective dikes. Damages will rise more steeply if the adaptation capabilities of the affected societies are exceeded.

There are several approaches to conceptualize and differentiate adaptation.

- Auffhammer, 2018 defines extensive and intensive margin adaptation. The extensive margin response is due to the installation of new equipment (e.g. new air conditioning systems, irrigation equipment, sea walls). The intensive margin response means that existing equipment is used more frequently (e.g. the more frequent operation of existing air conditioners and irrigation equipment).
- There is adaptation of individual consumers and businesses, but also national measures or strategies by governments.
- Adaptation measures can be separated in measures that act quickly (e.g. air-conditioning), as well as precautionary measures (usually infrastructure with a long lifespan).
- Adaptation may be aimed at gradual climate change (better insulation of houses against the increase in summer temperatures) or at protecting against extreme events (e.g. dikes against floods).
- There is managed (i.e. policy-driven) and autonomous (i.e. market driven) adaptation (National Academies of Sciences, Engineering, and Medicine, 2017).

[85] To take this into account, in the model PAGE all effects are modelled probabilistically.

- Finally, the IPCC differentiates between adjustment costs (short-term costs of adaptation) and macro-scale adaptation (long-term restructuring of economy).

To correctly model the costs and benefits of adaptation, all those different forms have to be taken into account, considering short-term and long-term impacts. Currently, costs-benefit adaptation studies mainly consider coastal areas (see Box 10) and agriculture.

Adaptation is incorporated in damage models in very different ways (see further Section 11):

- DICE considers adaptation implicitly. That is, the aggregate damage already includes the costs and benefits of adaptation (i.e. it is a "net" aggregate damage function, see Nordhaus, 2017). AD-DICE is an extension to DICE that explicitly considers adaptation. It disaggregates the damage function into adaptation costs and residual damages and selects a preferred combination of mitigation and adaptation (de Bruin et al., 2009).

- FUND introduces adaptation for certain sectors explicitly. It includes an explicit cost-benefit analysis of costly coastal protection against sea-level rise and assumes that part of the agricultural damages (associated with the rate of climate change) fade with time at zero costs (autonomous adaptation). For other sectors, adaptation is implicit as in DICE (Diaz & Moore, 2017; Estrada et al., 2019).

- PAGE introduces the notion of a *tolerable temperature* which increases with costly adaptation measures. Damages are a function of the difference between the real and the tolerable temperature, such that a real temperature increase of, say, one degree *without* adaptation causes the same damages as a real temperature increase of three degrees *with* adaptation, in a case where adaptation has raised the tolerable temperature to two degrees.

An extreme form of adaption is geoengineering. It is considered in damage models (e.g. MERGE, IMAGE) only as the removal or capture and storage of carbon dioxide (CDR/CCS), but to the best of our knowledge not as solar radiation management (SRM) or ocean fertilization.

Adaptation costs can be seen as indirect damage costs. Damage models thus often blur the difference between direct damages (e.g. destructions caused by storms) and adaptation costs. In FUND, for example, air conditioning is a major damage sector, even though strictly speaking this is an adaptation measure. The corresponding decrease in damages (improved health) is not considered in FUND, even though a representation of the health sector exists in the model.

The capacity for adaptation is a defining element and thus explicitly considered for the SSPs. For example, in SSP1 and SSP5 the capacity to adapt is high, as there is a well-educated, rich population, and strong technological development. In SSP1 there additionally is a good global governance and an intact ecosystem. In SSP3 and SSP4, on the other hand, the capacity is low due to the large, poor population, the lack of global cooperation, a weak technological development, and unequal distribution of resources (Riahi et al., 2017). These features have to our knowledge not yet been included into damage functions of damage models.

To summarize, damage models include adaptation explicitly (conducting a cost-benefit analysis of adaptation measures), implicitly (damage function is net of adaptation) or occurring autonomously (impacts fade at zero cost). In any case they use aggregated approaches that do not consider the variety of adaptation possibilities. If at all, damage models make very rough and ad-hoc assumptions on adaptation costs and benefits and do not include technological details.

The understanding of (future) adaptive capacity, particularly in developing countries, is limited (Watkiss, 2011).

Box 10: Sectoral damage cost models: Example of flood and coastal protection

Sectoral damage cost models can be used to examine a detailed set of impacts and adaptation measures. There is a large number of such sectoral analyses available at all scales. As they have no direct link to global climate cost estimates, sectoral approaches will not be examined in more detail in this report. In the following we will nevertheless exemplify the sectoral damage cost approach in the area of coastal and flood protection.

The economic analysis of flood and coastal protection has been the subject of scientific research for many decades and has been practised for centuries. The study design is usually based on flood modelling to identify the affected areas. The direct material damage is then determined by means of various damage functions, for example depending on land use or existing buildings. If necessary, indirect material damage resulting from the loss of human life is also derived. However, these damages are often considered separately and not as part of an integrated analysis. Damage events are also considered both with and without adaptation measures in order to derive the benefit of interventions on the basis of avoided damage. Uncertainties regarding the results mainly stem from the choice of the spatial scale: The larger the scale, the rougher the assumptions which have to be made. The smaller the scale, the more detailed the analyses are, but they run the risk of ignoring sectoral or regional feedback effects and mitigation measures outside the area under analysis. The above concerns hold true also for the results of some recent studies

As an example, the PESETA study (see Section 7.7.1) distinguishes five regions within the European Union. The areas of river and coastal flooding are considered separately. In the case of river floods, significantly higher expected annual losses are calculated for temperature increases of 2.5 °C, 3.9 °C, 4.1 °C and 5.4 °C in the period from 2071 to 2100 compared with the simulated base period from 1961 to 1990. Depending on the scenario, they lie between EUR 1.5 million and EUR 5.3 billion and reflect direct damage as a function of land use and flood water level. In the case of coastal floods, land use on the coasts is assumed to be constant. In an exemplary scenario with a steep rise in sea level (58.5 cm), the loss for northern Central Europe would be around 900 million euros, which mainly reflects the loss of productive land area. In relation to the gross domestic product (GDP), however, the loss is very small, amounting to a mere 0.01%. Although it can be further reduced by adaptation in the form of coastal protection investments, it cannot be eliminated due to the indirect economic effects.

7.7 Econometric approaches

The set-up of the damage function is a critically influential factor and, as explained above, the empirical foundation of existing damage models is quite weak and often outdated. There are data sources to improve upon this situation, depending on the type of damage function. For enumerative damage functions, new data on sector-specific damage estimates can be implemented and new sectors can be added (Section 7.7.1). Aggregate damage functions may use new results of macroeconometric studies that estimate the impacts of climate variations on GDP, without relying on an explicit representation of the underlying processes or sector-specific data (Section 7.7.2).

A detailed discussion on econometric methods with a focus on damage cost estimates is provided in Appendix C.

7.7.1 Sector-specific damage estimates

There are various studies that estimate climate damages for specific sectors and regions. These studies calculate damages in terms of percentage GDP reduction or absolute monetary values. None of those studies directly calculate the social cost of carbon but they can nevertheless be used to improve damage costs models with enumerative damage functions.

Carleton & Hsiang, 2016 compile results of recent studies for specific sectors and regions. They put a special focus on adaption and show how adaptation possibilities of societies differ within regions and change with time. The mortality during heat waves, for example, has decreased in the US due to more widespread air-conditioning. Mortality rates for intense cyclones (of the same strength) are higher in countries where overall exposure is lower. To properly estimate overall climate damages, it is thus crucial to account for the various and complex adaptation possibilities in each sector and region.

Similarly, Auffhammer, 2018b provides a broader overview on climate damages. In particular, he shows the current state of the damage function literature for specific sectors. He also stresses the importance of considering adaptation. As an example, he shows that, during the same heat wave, electricity consumption will increase more in a society that has adapted to climate change by widespread use of air-conditioning.

Hsiang et al., 2017 estimate damages in the United States related to the sectors agriculture, crime[86], coastal storms, energy, human mortality, and labour. They find a quadratic relationship between damages and global mean temperature change. Other recent publications have provided evidence for a non-linear relationship of climate change with a specific indicator as well. Some studies use a polynomial (usually quadratic) function with respect to temperature and precipitation (Burke, Davis, & Diffenbaugh, 2018; Burke, Hsiang, & Miguel, 2015; Pretis, Schwarz, Tang, Haustein, & Allen, 2018), others a non-parametric approach by assigning counts of daily temperature that fall into a pre-defined range of intensity bins (Deschênes & Greenstone, 2011; Schlenker & Roberts, 2009). In the case of agriculture, non-linearity may be captured by the concept of Growing Degree Days, which measures the duration that a specific crop is exposed to a defined productive range of temperatures (Burke & Emerick, 2016; Schlenker & Lobell, 2010; Schlenker & Roberts, 2009).

For Europe, there are several projects that derive sectoral damage cost estimates. The following brief descriptions draw heavily on the respective webpages where more details can be found:

- The PESETA project is now in its fourth round of development (https://ec.europa.eu/jrc/en/peseta-iv). It aims to better understand the effects of climate change on Europe for several climate change impact sectors, and how these effects could be avoided with mitigation and adaptation policies. PESETA feeds climate change and socioeconomic data into separate biophysical models to quantify sectoral changes (agricultural crop yields, energy supply, river floods, coastal floods, heat and cold waves, drought, habitat suitability, forest fires, forest ecosystems, water resources and windstorms). It assesses impacts of global warming at 1.5°C, 2°C, or 3°C. Each impact is either based on today's population and economy ("static" approach) or a projection for 2050

[86] Crime is usually not considered a "sector". Nevertheless, studies show that criminal activity is correlated to weather shocks.

or 2100 according to the ECFIN Ageing Report projections of population and economy ("dynamic" approach).[87]

- COIN (https://coin.ccca.ac.at). The project applies a disaggregated bottom-up approach to provide damage cost ranges for Austria in various sectors (agriculture, forestry, ecosystems and biodiversity, health, water supply and sanitation, energy, buildings, heating and cooling, transport and mobility, industry and retail, manufacturing and trade services, cities and urban green, catastrophe management, natural disaster protection and spatial planning, tourism). It also provides a framework to assess the costs and benefits of adaptation measures as well as to assess the impacts damages in other countries might exert on Austria (e.g. through supply chain distortions).
- Economics of adaptation to climate change (www.oekonomie-klimawandel.de). The project models the economic impacts of climate change and adaptation strategies in Germany. It focuses on the regional and sectoral distribution of costs and benefits of adaptation as well as on the institutional framework of the adaptation process.

Under the European Union Seventh Framework Programme (FP7/2007- 2013), the following projects have been conducted. They have all been discontinued and are thus outdated or partly dysfunctional. They nevertheless provide interesting information on several topics related to sectoral damages in Europe:

- ClimateCost (www.climatecost.cc) is a research project (active from 2008 to 2011) on the economics of climate change, funded by the European Community. The objective was, among other, to analyse the economic effects of climate change and the costs and benefits of adaptation. It focused on Sea Level Rise, River Floods, Energy, Health, Ancillary Air Quality Benefits, and Major Events and Tipping Elements.
- Impact2C (www.impact2c.eu) quantifies projected impacts under 2°C warming for Europe and the key vulnerable regions of the world, providing several case studies.
- IMPRESSION (www.impressions-project.eu). This project assesses the potential impacts of a warming of 4°C and more and the options available for reducing the risks.
- CLIMSAVE (www.climsave.eu): Assesses climate change impacts on and vulnerabilities of sectors such as agriculture, forests, biodiversity, coasts, water resources and urban development.
- ECONADAPT (www.econadapt.eu): Supports adaptation planning and provides practical information for decision makers.
- ToPDad (www.topdad.eu): Provides strategies for businesses and regional governments to adapt to the expected short term and long-term changes in climate. Seven case studies have been conducted, with a focus on the sectors energy, transport and tourism.

[87] As a 3°C warming scenario is unlikely to occur by mid-century, only the 1.5°C and 2°C targets are considered in 2050, while in 2100 all three warming levels are considered.

- BASE (www.base-adaptation.eu): Aims to foster sustainable adaptation in Europe by compiling and analysing data to improve the knowledge base and making information and strategies on adaption easier to access and understand.
- RAMSES (https://ramses-cities.eu): Quantifies the costs and benefits of a wide range of adaptation measures, with a focus on cities.

7.7.2 Macroeconometrics

7.7.2.1 Theoretical Background

Standard damage models such as DICE, FUND or PAGE rely on a damage function that — explicitly or implicitly — enumerates and aggregates sector-specific and regional damages. Given the limited data, this approach is contested (see above). A strand of the literature thus tries to estimate damages on a macroeconomic level, using data on deviation of GDP, temperature, and precipitation.[88] GDP deviations aggregate all sectoral effects, without the need to enumerate sectors, consider their linkages or explicitly understand the impact pathways. Along this line, there are essentially two approaches: the cross-sectional approach and the time-series approach (also called panel or fixed-effect approach).[89]

Cross-sectional studies regress GDP against temperature across countries for a given time period. It is assumed that all GDP differences between countries either stem from the climate or from other parameters that are explicitly accounted for in the regression. The latter is very challenging such that the so-called "omitted variable bias" is of paramount importance for cross-sectional studies. Nordhaus, 2006derives a damage function in a cross-sectional approach and finds damages to be slightly larger than in DICE's standard damage function — yet he cautions that the statistical uncertainty is high. Mainly because of the omitted variable bias, the cross-sectional approach has not been developed further in the literature.

Time-series data, on the other hand, have been used extensively in the last years to estimate damages function. The basic approach has been pioneered by Dell et al., 2012(henceforth DJO). They regress country specific, yearly temperature (and precipitation) deviations against GDP-deviations. DJO find that temperature increases seem to affect poor economies while rich economies are largely unaffected (see also Section 7.4).

Using similar data, Burke et al., 2015(henceforth BHM) make two major changes as compared to DJO: (1) For the econometrics, BHM assume a different underlying functional relationship and (2) they go further regarding the implication of the results. We will explain both in turn. For further details about these two studies and a discussion on the growth rate vs. level effect see also Section 7.4.

First, while DJO use a linear relationship between GDP and temperature, BHM use a "nonlinear" concave function. Specifically, BHM assume that a concave function best reflects micro-econometric data.[90] With this theoretical setting, BHM find a hump-shaped function with an

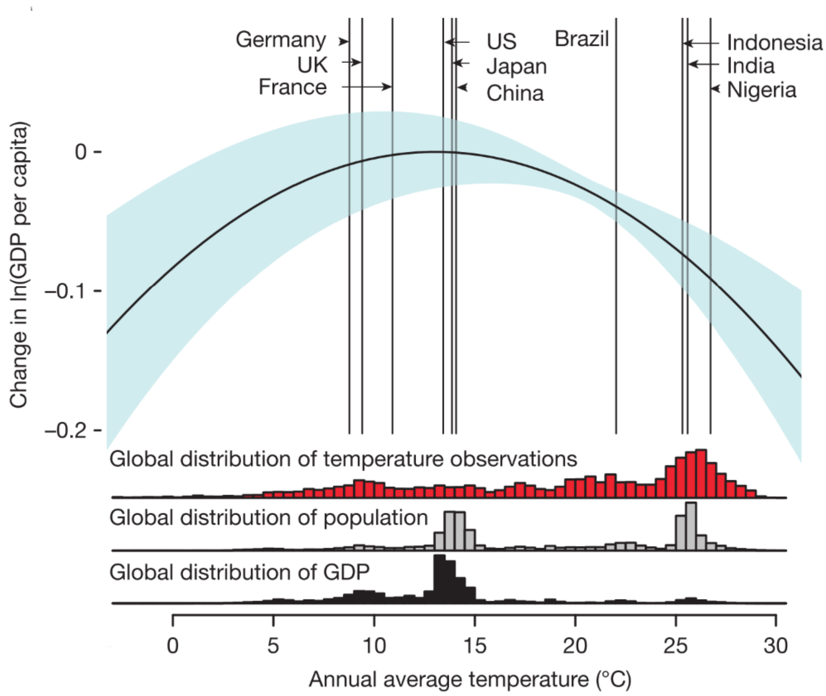
[88] It has been known for a long time that, on average, warmer countries have a lower GDP (see e.g. Dell et al., 2012, Figure 1). Yet, in this setting, *deviations*, not *absolute* values are of interest.

[89] There is also a hybrid approach called long differences that is a cross-sectional comparison of changes over time and aims to balance between the strengths and weaknesses of the other two designs (Hsiang, 2016).

[90] Micro data suggests that there are non-linear sectorial responses on short time scales, such that damages on the micro level can be abrupt (crop yields, labour supply). According to DJO, these abrupt micro level changes aggregate to smooth yearly, large-scale damages on the macro level.

optimal annual average temperature of approximately 13°C as given in Figure 18.[91] The y-axis of the figure represents the lasting impact on the growth rate for a given change in temperature. See also extended figure 1 of BHM for further explanation of the method and the underlaying data.

Figure 18: Effect of annual average temperature on economic production according to Burke et al., 2015



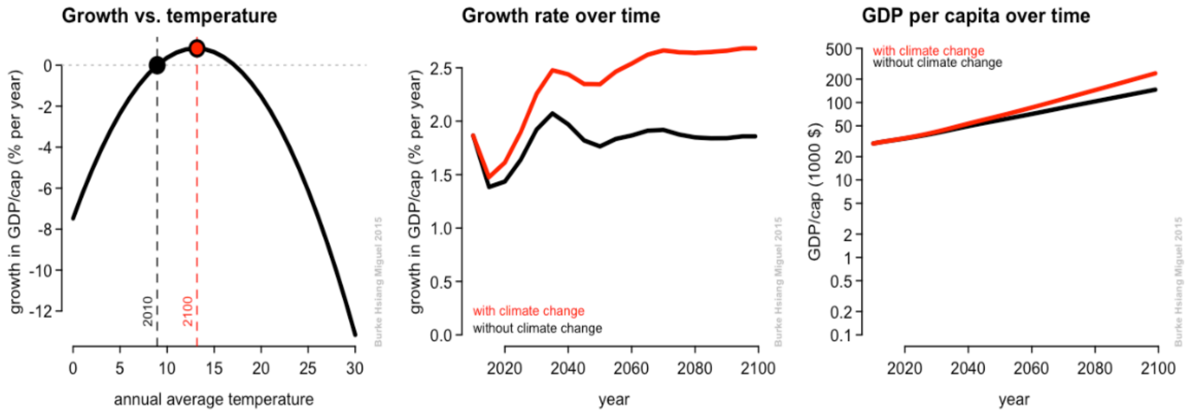
Specification: "pooled/short run". See text for explanation.

Source: Burke et al., 2015

Second, especially important in our context, BHM explicitly foresee using this growth vs. temperature relationship as basis for a damage function. Figure 19 illustrates the idea for the case of Germany using BHM's best-guess relationship. It compares two growth paths, one without climate change (using growth rates from SSP3/SSP5) and one with climate change (using temperature change for RCP 8.5). The temperature change has a lasting impact on the GDP growth rate over time and thus the impact on GDP per capita accumulates with time. In the case of Germany, the impact is beneficial (for 2100 the best guess is +63% GDP per capita as compared to the case without climate change), as Germany is currently below the temperature optimum. This result is clearly different to any previous studies. It is also not robust, as the optimal temperature is uncertain. As explained below, this uncertainty is a major drawback when applying BHM's method for damage modeling on a reginal scale and by implication also on a global scale.

[91] Several studies have followed the approach of Burke et al. (2015), estimating a productive threshold between 13°C and 16.3°C (e.g. Pretis et al. 2018).

Figure 19: Burke et al., 2015's best-guess relationship applied for Germany under RCP 8.5



Specification: "pooled/short run". See text for explanation.
Source: http://web.stanford.edu/~mburke/climate/map.php

While currently cold countries thus profit from climate change, the currently warm countries experience decreases of GDP per capita (often the decrease is more than 80%) such that globally aggregated GDP per capita decreases by 23% in 2100 compared to the case without climate change — in this setting.

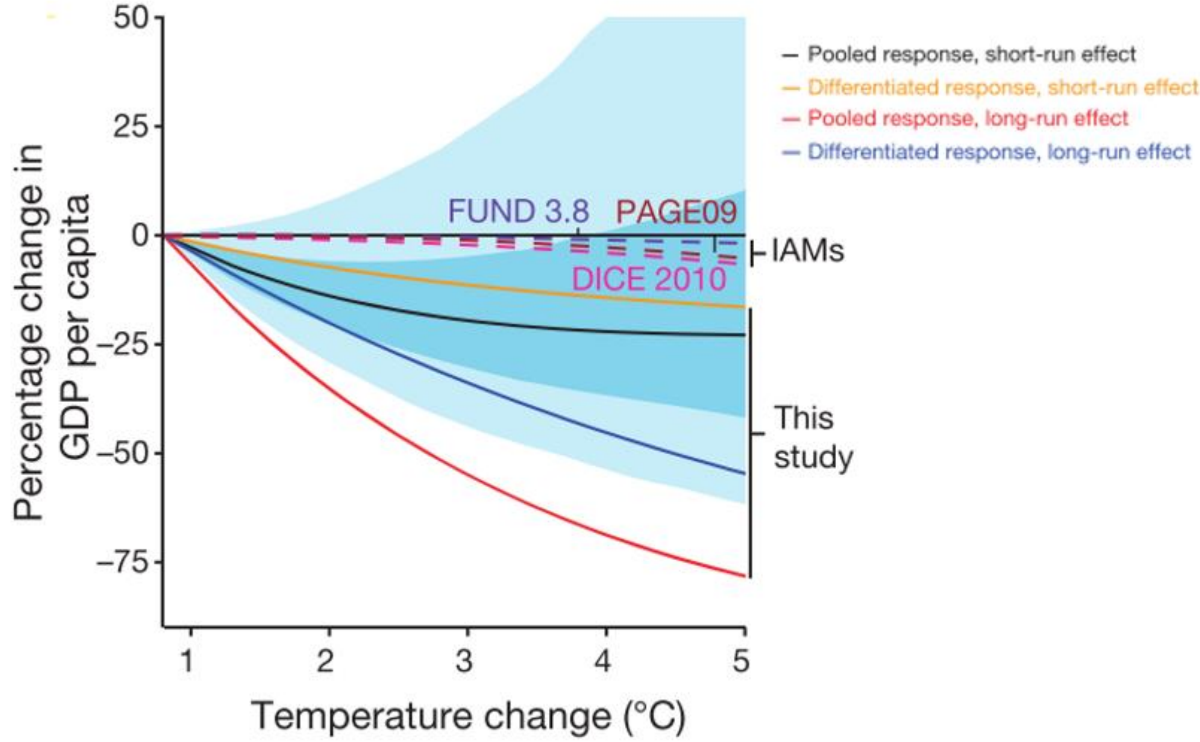
BHM consider in fact several specifications: (1) a specification where the relationship is estimated separately for rich and poor countries (differentiated) vs. a specification where countries are not separated (pooled) and (2) a specification where only the temperature deviation of the last year are considered (short run) vs. a specification where the last 5 years are considered (long run). Combining these specifications, BHM present four different growth vs. temperature functions, which are all hump shaped. Using the specifications as damage function, results range from 18% to 75% loss of GDP in 2100 (see solid lines in Figure 20). Note that Figure 18 depicts the "pooled/short run" specification.

Figure 20 shows four additional prominent features of the damage function derived by BHM. First, global damages are considerably higher than in the enumerative or aggregate damage functions used in the "standard" model (DICE, PAGE or FUND; see dashed lines). This is because BHM assume that climate change affects the growth *rate*, whereas the standard models only feature a level effect (see also Section 7.4). Second, the statistical uncertainty is substantial (see blue shaded areas for the "pooled/short run" specification; dark blue is 25th to 75th percentile (interquartile range) and light blue is 5th to 95th percentile). Third, the damage function is concave. That is, additional damages decrease with an increase of temperature. This is in stark contrast to the damage function of DICE, PAGE or FUND, which are all convex. BHM feature a concave damage function because of the assumption that temperature affects the growth rate and not the level.[92] And fourth, the damages for the two long-run specifications (blue and red line) are substantially higher, as in this case the beneficial effects of climate change on colder countries fade away while the detrimental effects for warmer countries remain (see Extended

[92] Assume the basic growth rate is 5%. The impact on GDP is larger for a growth rate reduction from 5% to 4% than for a further reduction from 4% to 3%. Thus — in a setting where climate change impacts the growth rate — as temperature increases, the impacts are ever less relevant. For a more detailed explanation of this effect, the interested reader is deferred to Burke et al., 2015, Extended Data Figure 6e and Chapter D.4 in the supplementary material.

Data Figure 2 in Burke et al., 2015). Regarding the impact of the specifications pooling vs. differentiation there is no straightforward explanation.[93]

Figure 20: Projected global GDP loss in 2100 as compared to case without climate change – comparing marcoeconometric and other studies



For SSP5 scenarios. See text for explanation.
Source: Burke et al., 2015

For SSP5 scenarios. See text for explanation.
Source: Burke et al., 2015

There are several challenges using BHM's relationship as the basis for a damage function.[94]

First, it is conceptually unclear if using annual deviations are indicative for long-run changes of the climate. A 1°C annual temperature increase in a given year may have different effects than increasing the average temperature of that country by 1°C (Dell et al., 2014; Newell et al., 2018). This has several reasons (taken from Dell et al., 2014):

- Economies and societies may partly **adapt** to long run changes given enough time, new technologies or behavioural changes. A drought may for example cause substantial loss in agricultural production if there are no or only inefficient irrigation systems in place. If precipitation decreases permanently, suitable irrigation systems may be installed such that the agricultural production level can be maintained.

[93] A relevant parameter in this respect is the threshold that separates between poor and rich countries. BHM used the median of the current distribution and assume this threshold remains constant. If a poor country grows such that its GDP surpasses this threshold, it "graduates" to become a rich country. Therefore, the pool of poor countries shrinks with time. It is not stated in the paper if this procedure accounts for the effects of climate change. Presumably, it does not.

[94] For an additional resource of some relevant questions related to BHM's methods see also the FAQ at http://web.stanford.edu/~mburke/climate/BurkeHsiangMiguel_FAQ.pdf (11.02.2020).

- A countervailing effect is **permanence**. The same type of changes may have much smaller effect over a limited time-period compared to a permanent change. Take again agriculture as an example, but in a different setting. A single-year drought has little effect on the agricultural output if appropriate irrigation systems are in place. If precipitation decreases permanently, the available water reservoirs may however not suffice to maintain the agricultural production over a longer time horizon.
- **General equilibrium adjustments** of prices and factor reallocations will not be noticeable in annual deviation but may have significant influence in the long run.
- Finally, if climate change produces temperature increases that are beyond historical annual deviations, it is unclear whether the thus necessary **extrapolation** is appropriate.

Second, as indicated in the above figures, the statistical uncertainty is very high. And the global damage function is sensitive to the (uncertain) optimal temperature, as many high GDP countries cluster in the temperature range of 12—15°C (see Figure 18, black histogram).

Third, there is considerable structural uncertainty. BHM assume a quadratic functional form for their regression and a certain way to include control variables. They also test several other functional forms and controls and conclude that qualitative results remain the same. To quantify the structural uncertainty, Newell et al., 2018 systematically test a total of 400 model specifications for the regression analysis[95] and find that global GDP damages in 2100 are in the range of –48% to +157% (see Figure 21), not even accounting for statistical uncertainty. Using a hindcast procedure, Newell et al., 2018 test BHM 's specific model specification and find that its performance is mediocre compared to the other 399 specifications.

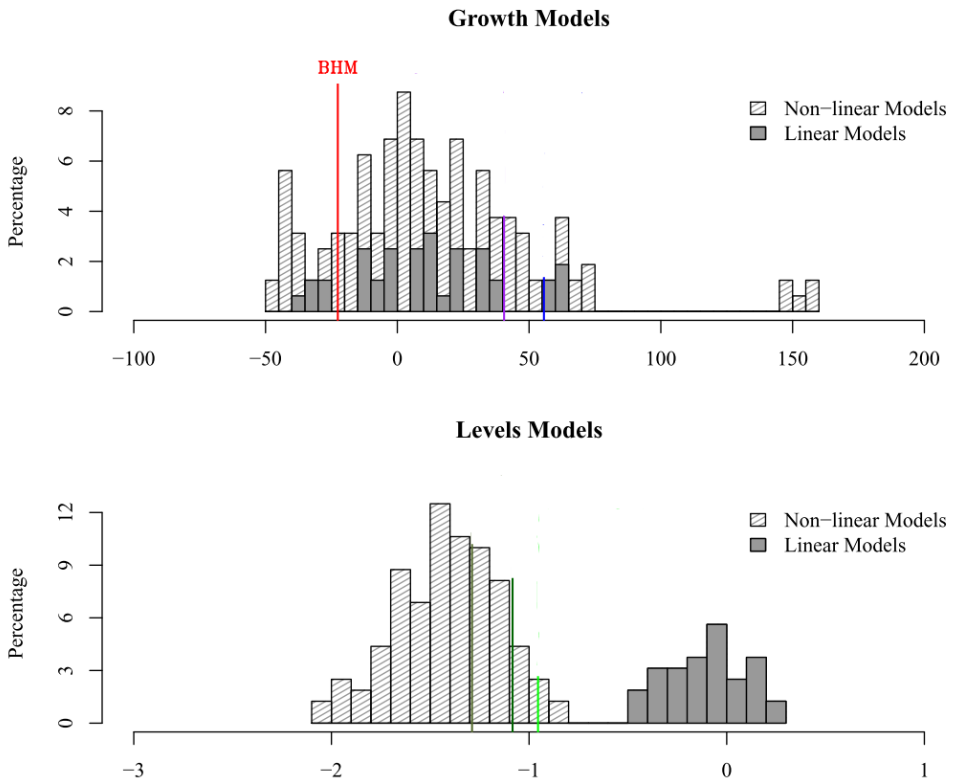
Forth, and related to structural uncertainty, BHM assume that temperature variability affects the GDP growth rate. This leads to high SCC values, as growth rate effects accumulate with time, whereas level effects do not. It is debated in the literature if climate change exhibits level or growth effects or some mixture (see further Section 7.4).

Fifth, there are several impact categories that are not covered by the macroeconometric approach: Non-market damages, tipping points, ocean acidification, sea level rise and macro-scale adaptation (see e.g. Ricke et al., 2018, table S5 (supplementary material)[96]). Including these impacts would increase the damages.

[95] The 400 model specification results from combining the following sub-specifications; GDP growth versus GDP level effect (2 specifications); Temperature function (5 specifications: none, linear, quadratic, cubic, spline); Time and region controls (8 specifications); precipitation function (5 specifications: none, linear, quadratic, cubic, spline). "none" refers to a model where temperature or precipitation have no impact on GDP.

[96] They also list short term adjustment costs and general equilibrium effects (spill over or trade) but depending on the econometric model set-up those may be included.

Figure 21: Global GDP Damage Estimates for 2100 using various marcoeconometric approaches (note different scales on the x-axes)



GDP Damage Estimates for the year 2100 using the RCP8.5/SSP5 scenario. The BHM estimate for the "pooled/short run specification" is indicated in red.
Source: Newell et al., 2018, Figure 2.

7.7.2.2 Application in the literature

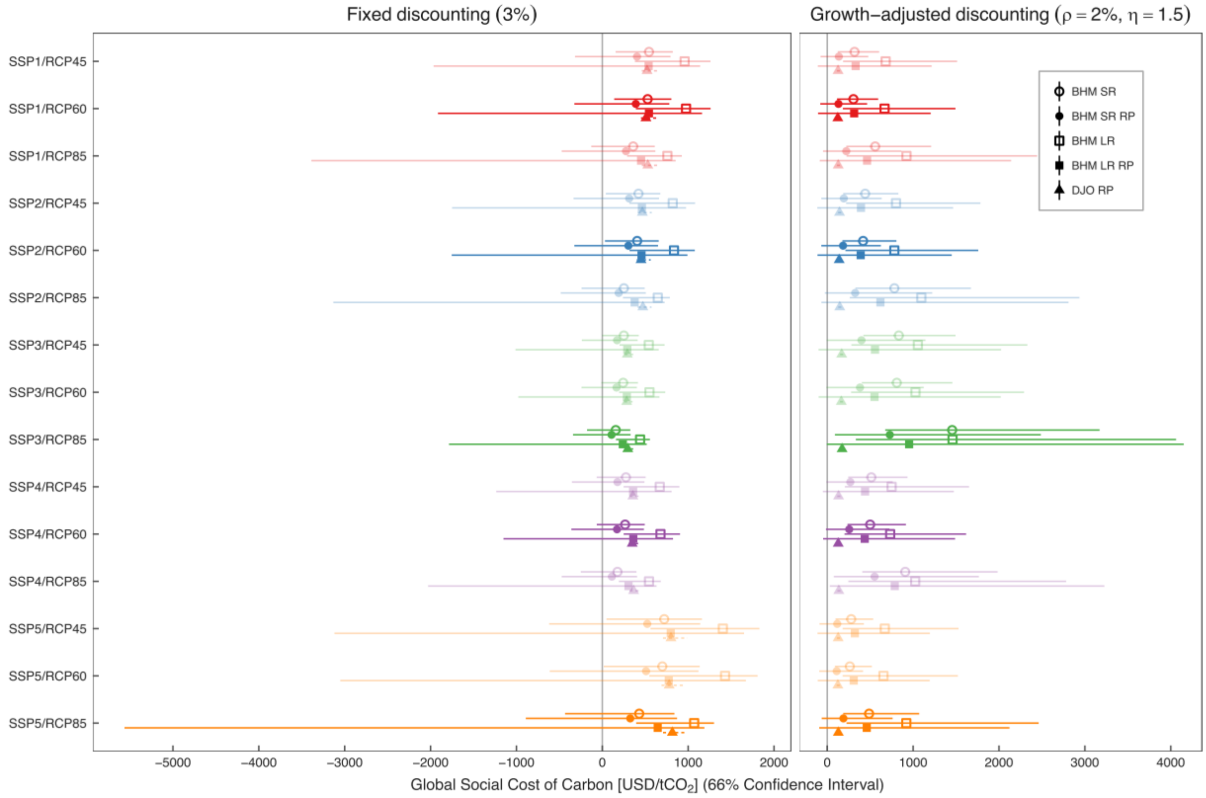
A new strand of literature followed the example of BHM and used the econometric approach to derive SCC (and in some cases endogenous temperatures).

Burke et al., 2018 use a stochastic approach considering different SSP-scenarios, discounting schemes and parameters, climate model outcomes and the statistical uncertainty from a macroeconometric approach. They find that: (1) For a warming of 2°C relative to 1.5°C, global damages are higher with a probability of 75%, a majority of countries likely profits, and — using a 3% discount rate — the accumulated benefits exceed 20 trillion $US\$_{2010}$ with 60% probability. (2) Compared to a scenario where warming remains at the 2000–2010 levels, a warming of 2.5–3 °C by 2100[97] results in a GDP loss of 15%–25%, and a warming of 4 °C results in a GDP loss of more than 30%.

Ricke at al., 2018, derive various estimates of the SCC (see Figure 22). They differentiate between socioeconomic scenarios (SSP), concentration scenarios (RCP), discounting schemes as well as the five macroeconometric model specification (the four specifications as given by BHM and one as given by DJO (see Section 7.7.2.1)). The range of the results illustrates the impact of statistical and structural uncertainty. Note that several elements of uncertainty such as catastrophic events or non-market impacts are still missing.

[97] Corresponds to the predictions under the current national commitments NDCs.

Figure 22: SCC Estimates using a macroeconometric damage function for various scenarios and discounting schemes



The points represent the median estimates of the SCC. The lines represent the 13.7%-83.3% confidence intervals.
SR=Short run; LR=Long run; RP= differentiated; Explanation see Section 7.7.2.1.
Source: Ricke et al., 2018, Figure S2 (supplementary material).

Ueckerdt et al., 2019 combine the model REMIND with BHM's damage function (specification: differentiated/short-run) and run a stochastic cost-benefit analysis. They find that the endogenous temperature increase is in the range of 2°C and show that these results are insensitive to parametric uncertainty (most notably the pure rate of time preference and the intertemporal inequality aversion). However, they assume and explicitly state that their results crucially depend on BHM's assumption that climate change affects the growth rate and not the level.

Glanemann et al., 2020 conduct a similar exercise and replace DICE's with BHM's damage function (all four specifications) in a stochastic setting. The authors find that "the goal to limit warming to 2 °C or less is cost-benefit optimal for a wide set of damage functions" (ibidem, p. 3). The optimal 2100 warming for a climate sensitivity of 2 °C has a median of 1.7°C (range: 1.3 °C to 2.5 °C), for a climate sensitivity of 2.9 °C the median is 2.1°C (range: 1.8 °C to 3.0 °C), and for a climate sensitivity of 4 °C the median is 2.5°C (range: 2.3 °C to 3.4 °C).

Kalkuhl & Wenz, 2020 employ several regression model types using a novel data set. They subsequently derive several possible damage functions and replacing the standard one in DICE-2016R. The resulting SCC-estimates are 73–142$/$tCO_2$ in 2020, rising to 377–780$/$tCO_2$ in 2100. Even though these numbers exclude non-market damages and damages from extreme weather events or sea-level rise, they are a factor two to three higher than results with DICE-2016R's standard damages function.

8 Scenarios and time of emission

The SCC varies with the baseline CO_2 concentrations over the atmospheric lifetime of the additional emissions and the associated change in marginal damages. SCC values thus depend on the underlying emission scenario and the point in time the emissions take place.

8.1 Emission scenarios

Damage models need emission scenarios as input (see Section 2.4).[98] To see the impact of this choice, consider how the following elements are impacted by the underlying emission scenario:

1. An additional unit of emission increases temperature. Earth science tells us that this temperature increase is approximately independent of the underlying emission scenario (i.e. the relationship between temperature and cumulative emissions is roughly linear; see further TCRE in Section 6.2).[99] Unaware of this recent finding, most damages models depict a slightly concave relationship between temperature and cumulative emissions. Consequently, for the emission of a ton of CO_2 choosing a higher emission scenario results in a lower marginal temperature increase.
2. Damages models usually assume that the relationship between temperature and damages is convex.[100] The marginal damages are thus higher choosing a high emission scenario (as this scenario features higher temperatures).
3. Finally, the stream of future marginal damages is discounted. Using the Ramsey equation (see Section 5.1.2), the discount rate decreases in a high emission scenario (larger damages of such a scenario slow down growth and thus the growth discounting component of the Ramsey equation decreases). Therefore, the present value of the stream of future marginal damages (that is the SCC) increases. This effect is especially relevant if the PRTP is low, in which case the large damages of a high emission scenario in the far future are accounted for.

A higher emission scenario increases the SCC if the second effect „outweighs" the first, subject to the third (DECC, 2009). Anthoff et al., 2009 (see their table 6) find a significant increase of the SCC for high emission scenarios. Using PAGE, the Stern review finds for a business-as-usual scenario[101] SCC of $\$_{2000}85/tCO_2$, while for a 550ppm trajectory the SCC are \$30 and for a 450ppm trajectory \$25 (Box 13.3 in Stern, 2007).

8.2 Emission Time

SCC values are usually higher if emissions take place in the future (Watkiss, 2011; Watkiss & Hope, 2011).[102] The SCC increase with time for analogous reasons as explained for the emission scenarios: An additional unit of emission in future years leads to larger impacts due to the damage models' nonlinear temperature functions (as climate change will be more severe in the future).[103] This depends of course on the underlying emission scenario. The more pronounced

[98] CB-IAM determine the emission scenario endogenously. For damage models, emission scenarios are an exogenous input (see Figure 4 and Section 3.2). The following arguments are valid for both cases.

[99] This does not consider tipping points or carbon cycle feedbacks, which may lead to a convex relationship if aggregate emissions are high.

[100] This is either an explicit feature of the model's aggregate damage function (e.g. $Damages = a * \Delta T^b$ with b>1, e.g. in DICE) or arises implicitly from aggregating sector-specific damage functions (e.g. in FUND).

[101] 550ppm CO_2eq by 2035, then increasing at 4½ppm per year and still accelerating.

[102] Note that this holds true only if future SCC values are calculated in the sense of a "current value" (i.e. damages arising from emissions in the future are discounted back to the year of emissions). Future SCC values reduce (strongly) if they are subsequently discounted back to the present period.

[103] A counterexample is Tol, 1999, which finds that SCC *decrease* with time.

the future increase of emissions, the more the SCC increases with time. Additionally, GDP growth raises the value of economic capital that is sensitive to climate change or the willingness to pay, both of which in turn increases the absolute value of the SCC. This is taken into account in damage models, where damages are (partly) modeled proportional to gross GDP.

As SCC are often used for decisions that influence emissions far into the future (e.g. long-lasting infrastructure or policies), this time-dependence is policy relevant. Accordingly, it is best practice for policy applications to publish trajectories of the SCC (see Section 3).

9 Non-CO_2 greenhouse gases and aviation

9.1 Non-CO_2 greenhouse gases

The focus of climate damage cost estimates is on CO_2. Yet, non-CO_2 greenhouse gases, such as methane or nitrous oxide, have a considerable effect on climate change too.[104] It is thus important to also consider their social costs. There are two common approaches.

1. The social costs of non-CO2 greenhouse gases can be determined directly in damage models using the same method as for the SCC.[105] This is e.g. the method used by the US-IAWG for methane and nitrous oxide. For a detailed description, see Marten et al., 2015and IAWG, 2016.[106] The related uncertainties are essentially the same as for the calculation of the SCC.
2. The SCC can be multiplied with the respective global warming potential (GWP) of the non-CO_2 GHG. Roughly speaking, the GWP indicates how much more global warming a non-CO_2 GHG causes as compared to CO_2.[107] The GWP depends on the specified time horizon, as greenhouse gases differ in their heating potential and atmospheric residence time. Methane, for example, has a rather short atmospheric residence time of approximately 12 years such that its GWP over a 20 years horizon is 84, whereas over a 100-year horizon it is only 28.[108] Usually a time horizon of 100 years is taken, yet this choice is essentially arbitrary.[109]

Using GWP for conversion (unit of GWP: “tGHG per tCO_2”) is a well-established method when dealing with non-CO2 GHG for reporting purposes (e.g. GHG inventories). GWP is thus easy to communicate. It is, however, conceptually problematic to divert the concept of GWP from its original intended use and instead use it in the climate modelling context as a “currency” to convert the SCC into social costs of non-CO2 GHG (Cara et al., 2006). In the latter case the implicit unit of GWP is “$/tGHG per $/tCO2”. The emission of a non-CO_2 GHG does not — as a GWP-conversion-factor of GWP implies — yield damages as a fixed multiple of the damages caused by CO_2. To see this, note that the GWP_{100} is the same irrespective of whether the climate impact occurs in year 1 or in year 99. This contrasts with two essential features used to calculate the social cost of carbon:[110]

- Compared to discounting theory, the GWP_{100} implies a discount rate that equals zero within the next hundred years and jumps to infinity subsequently. Economic discounting applies a discount rate greater than zero, which remains constant or declines with time (either due to growth discounting or in a predefined way). Ideally, the time horizon for calculating the GWP

[104] Other, less relevant, gases are e.g. HFCs, PFCs and SF6. In addition, there are further climatically active substances such as sulphates, organic carbon or black carbon.

[105] This is not possible with the standard versions of DICE and PAGE as they prescribe exogenous projection of aggregate non-CO2 radiative forcings. Only FUND explicitly considers CH4 and N2O.

[106] A related study is Waldhoff et al., 2014, which uses FUND3.9 to determine the social costs of several greenhouse gases.

[107] More precisely, the GWP is defined as the quotient of the cumulative radiative forcing caused by one ton of a GHG as compared to one ton of CO_2 over a specified time horizon. Radiative forcing due to a GHG is a measure of the instantaneous radiative imbalance at the top of the atmosphere, which causes the atmosphere to heat up.

[108] https://en.wikipedia.org/wiki/Global_warming_potential (13.11.2020)

[109] The Kyoto protocol used a time horizon of 100 years such that GWP_{100} has become the de-facto standard. A shorter time horizon (e.g. 20 years) gives a higher relative weight to short-lived climate gases (such as methane) and vice versa.

[110] There are several other issues which we do not discuss here any further (e.g. some impacts such as CO_2-fertilization in agriculture or ocean acidification are CO_2-specific).

should be consistent to the time horizon implied by the discount rate chosen to calculate the SCC in the damage models.[111]

- The impact of a given amount of climate change is assumed to be higher in later years due to the presumably convex shape of the damage function.

Table 14 provides an overview of the GWP and compares IAWG estimates of social costs for methane (SC-CH_4) and nitrous oxide (SC-N_2O) with the SCC. The social costs of further GHGs are not discussed here.[112] These numbers show that the SC-CH_4 for emissions in 2020 are 26-45 times higher than for CO_2, depending on the discount rates. For emissions in 2050, the SC-CH_4 are 31-52 times higher than the SC-CO_2 (not shown). These numbers are higher than GWP_{100}=25. Therefore, a GWP_{100}-based approach underestimates the damages of CH_4-emissions, especially for higher discount rates and future emission years.

For N_2O, changes in the discount rate have a smaller impact on the SC-N_2O relative to the SCC. Similarly, the GWP changes less with the time horizon. This is because of the much larger atmospheric lifetime of N_2O. Again, the GWP-based approach underestimates the damages of N_2O emissions.

Table 14: Properties of non-CO_2 GHGs

GHG	Atm. lifetime	Global Warming Potential			Social Cost non-CO_2 GHG relative to SCC (Average Value for 2020) as given by US-IAWG		
		Time Horizon			Discount rates[113]		
		20 years	100 years	500 years	5%	3%	2.5%
Methane CH_4	12 years	72	25	7.6	45 (=540/12)	29 (=1200/42)	26 (=1600/62)
Nitrous Oxid N_2O	114 years	289	298	153	392 (=4700/12)	357 (=15000/42)	355 (=22000/62)
CO_2	complex*	1 (per definition)			-	-	-

* Around 50% remain after 100 years, around 30% for at least several thousand years (see further Section 6.1)
Source: www.epa.gov/ghgemissions/overview-greenhouse-gases (19.12.2019); (Forster et al., 2007) ; IAWG, 2016.

Thus, despite being conceptually the wrong tool, using GWP to convert SCC into the social costs of other GHG may be justifiable on the grounds that direct social cost calculations yield similar results. Published research surrounding this topic is sparse, however.

9.2 Aviation[114]

Aviation is responsible for approximately 12% of global transport-related CO_2-emissions and 2% of total CO_2-Emissions (ICAO, 2013). Aircraft exhaust emissions in the cruise phase (i.e. above 9000 m altitude), which do have climatic impacts beyond those caused be the CO_2-

[111] A high discount rate should imply a shorter time horizon and vice versa. We are, however, not aware of any paper that discusses this issue.

[112] See also IPCC's Assessment Report 4, Working Group II contributions (Yohe et al., 2007),, Chapter 20.6, which briefly reviews the sparse literature as of 2007and estimates the social cost of SF_6 as US$200,000 per tonne emitted in 2001.

[113] These three values correspond to the default choice of the US-IAWG.

[114] This Section draws on Althaus & Cox, 2019.

Emissions alone (for CO_2-emissions the emission-altitude plays no role). The most relevant reasons are the following impacts of additional aircraft exhaust emissions:

- **Contrails and Aviation Induced Cirrus (AIC):** Contrails are line-shaped condensation trails that only form in high altitudes, where the air is very clean and dry such that additional nuclei and water vapor from aircraft exhaust trigger rapid cloud formation. AIC are cirrus clouds caused by spreading contrails. Whether contrails and subsequently AIC form and how long they persist depends on the state of the surrounding air masses. Contrails and AIC have a positive net radiative forcing because they trap outgoing terrestrial radiation more than they reflect incoming solar radiation. There is significant variability in the radiative forcing effect due to – among other things – the time of the day[115], state of the surrounding atmosphere, or the presence of other clouds. Forster et al., 2007 reports a GWP_{100} of 0.21 for contrails and 0.63 for AIC. (Lund et al., 2017) report a GWP_{100} value for contrail cirrus, consisting of contrails and AIC, of 0.84, which amount to the same total, albeit using a different method.
- **NO_x-emissions** at high altitudes induce ozone formation and methane destruction. These two processes cause a positive and negative radiative forcing, respectively, which partly cancel each other out. There is significant variability in the literature regarding the net climate impact. Estimates of theGWP_{100}-factor range from -2.1 to 71 (Fuglestvedt et al., 2010), -21 to 67 (Myhre et al., 2011) and 4 to 60 (Skowron et al., 2013). Lund et al., 2017 report a GWP_{100} of 77, which according to Althaus & Cox, 2019 seems to be the most methodologically sound publication on the topic.
- **Particulate matter / black carbon (PM/BC)-emissions** cause a positive radiative forcing, as they absorb short-wave radiation and alter cloud structures. (Lee et al., 2010) and Fuglestvedt et al., 2010 both report a GWP_{100} value for of 460, while Lund et al., 2017 report a value of 1060.
- **Water vapor** emissions at higher altitudes cause a much higher radiative forcing than at lower altitudes, and more so over the tropics than over the poles. The radiative forcing and lifetime of aircraft water vapour emissions depend strongly on flight altitude and latitude. Fuglestvedt et al., 2010 compute a GWP_{100} value of 0.2.
- **SOx and Organic Carbon** both cause negative radiative forcing due to formation of particles, which reflect solar radiation and change cloud properties (Fuglestvedt et al., 2010). Lund et al., 2017 report a GWP_{100} value of -152 for SOx and a value of 77 for organic carbon.

It is common to consider these additional impacts in the cruise phase using a CO_2 emission weighting factor (EWF), which multiplies to the climate impact of CO_2 alone.[116] This is convenient as CO_2-emissions are well-known and it eases communication of these additional impacts.

[115] While contrails trap substantial amounts of warming infrared energy during both day and night, only during the day there is an offsetting cooling effect as contrails also reflect some sunlight back into space.

[116] Still in use is also the so-called radiative forcing index. This is however methodological inferior to using EWF, as the radiative forcing index only considers the instantaneous impact. The radiative forcing index is thus most likely higher than the EWF, as most additional impacts are rather short-lived.

Calculating an EWF faces however several challenges. First, the level of scientific understanding of the additional aircraft exhaust emission's impact is partly low (e.g. contrail formation depends on the atmospheric conditions; and their impact on the time of the day, altitude and background albedo etc). Second, while the impact of CO_2-emissions is on very long time scales, the impacts of the additional aircraft exhaust emission are short-lived. Comparing them is thus a methodological challenge.

One methodology to calculate the EWF is to multiply the respective aircraft exhaust emissions relative to the cruise phase emission of CO_2 (first line in Table 15) with the GWP_{100} factor of the aircraft exhaust (second line). The resulting EWF are presented as the last line. Althaus & Cox, 2019 find a most likely total value of 2.0, with a range of 1.3 to 3.6 (not shown).

Table 15: CO_2-emissions weighting factor (EWF) for aviation

	CO2	Contrails & AIC	NOx (as N)	PM/ BC	Water Vapor	SOx	Organic Carbon	Total EWF
Cruise phase emissions relative to CO_2	1	1*	1.2E-03	3.7E-05	0.39	2.7E-04	3.1E-05	-
GWP_{100}	1	0.84	77	1060	0.20	-152	-77	-
EWF	1	0.84	0.094	0.039	0.08	-0.041	-0.0023	**2.01**

*For contrails & AIC the emission of "one ton of contrails & AIC" is not a sensible quantity. To be consistent with other emissions, the GWP_{100} of contrails & AIC is calculated per ton of CO_2 emitted in the cruise phase.

Source: own illustration, Infras based on INFRAS 2019; Emission data by Cox et al., 2018; GWP_{100} as stated in the main text.

Other approaches (and an overview on newest scientific findings on that topic in general) are described in Lee et al., 2021. One may use the global temperature potential (GTP) instead of GWP. The GTP describes the change in temperature at a point in time (e.g. in 100 years for GTP_{100}) due to the additional aircraft exhaust emission. GWP, on the other hand, is the integral of the additional radiative forcing over the whole timespan. For long time scales, the GTP for short-lived substances is thus much lower than the GWP and hence also the EWF on that basis. Finally, Lee et al., 2021 notes that assumptions considering the past and future rate of change of additional aircraft exhaust emission are needed; and a fixed EWP is only appropriate if future aviation emissions increase exponentially.[117] Their main results (EWF=3) should only be applied to future scenarios that are roughly in line with the current trend (before COVID-19).

Note that at first glance the EWF-approach is similar to the one GWP-approach as described in Section 9.1, as in both cases certain factors are multiplied with values related to CO_2. Yet, the underlying idea is quite different. Whereas GWP allows to compare the emission of a ton of non-

[117] Lee et al., 2021 consider "the fact that constant emission of short-lived climate forcers maintain an approximately constant level of warming, whilst constant emissions of long-lived climate forcers, such as CO2, continue to accumulate in the atmosphere resulting in a constantly increasing level of associated warming. Hence […] the widely-used assumption of a constant 'multiplier', assuming that net warming due to aviation is a constant ratio of warming due to aviation CO2 emissions alone, only applies in a situation in which aviation emissions are rising exponentially such that the rate of change of non-CO2 RF is approximately proportional to the rate of CO2 emissions […]. In contrast, under a future hypothetical trajectory of decreasing aviation emissions, [the] multiplier could fall below unity, as a steadily falling rate of emission of (positive) short-lived climate forcers has the same effect on global temperature as active removal of CO2 from the atmosphere. The […] 'multiplier' calculated here (which depends on the ratio of the increase in net aviation warming to the increase in warming due to aviation CO2 emissions alone over the recent past), should not be applied to future scenarios that deviate substantially from the current trend of increasing aviation-related emissions."

CO_2 GHG to a ton of CO_2 for accounting purposes, the EWF considers additional climate impacts of aviation using the emissions of CO_2 as a basis.

10 Cost-benefit IAM

CB-IAM (pro memoria: *cost-benefit integrated assessment models*) are designed to determine costs and emissions endogenously. They are not the focus of this study and we thus discuss them only briefly here (see also Box 2). CB-IAM weigh the mitigation costs against the benefits of reducing climate damages (sometimes including adaptation measures) within one model (see e.g. Nordhaus, 2014 or Millner & McDermott, 2016).[118] Results of CB-IAM are on the one hand influenced by the same factors as damage models. On the other hand, they also include a representation of the *mitigation* costs. This representation is usually kept quite simple to remain tractable and because the focus is on the long-term. If — ceteris paribus — modelled mitigation costs are higher, the endogenously determined emission trajectory will also be higher. This entails that endogenous damages are higher as well.[119]

The specification and calibration of the mitigation cost function essentially have the same types of uncertainties as the damage function. A crucial aspect is how abatement costs change with time (or with cumulative emission reductions) and if this occurs autonomously or following endogenous technological progress. This and other influencing factors are also presented further in Part 3.

Damage models usually contain a mitigation module as well and can thus be used in "cost-benefit mode". Compared to the mitigation cost models presented in Part 3, the mitigation module of CB-IAMs is, however, rather simple. The mitigation modules of DICE, FUND and PAGE are briefly presented in Section 11.

In fact, Nordhaus wanted to "weigh the options", explicitly developing DICE as a CB-IAM. Nordhaus has thus in regular intervals published his estimate of the "optimal" temperature trajectory. Basically, this "optimum" has not changed since he devised DICE in the 1990s. Figure 23 shows his most recent estimates. Apparently, there is a stark contrast to the threshold of 1.5°C (or 2° at maximum) as advocated by most climate scientists and subsequently demanded by the Paris Agreement.[120] The reasons are namely the moderate damage function and the high discount rate used by Nordhaus. Even though Nordhaus explicitly cautions that his calculations are uncertain, he continues to publish and present these estimates, implying that climate scientists' targets are not "economic" and thus too ambitious (see also Hänsel et al., 2020).[121]

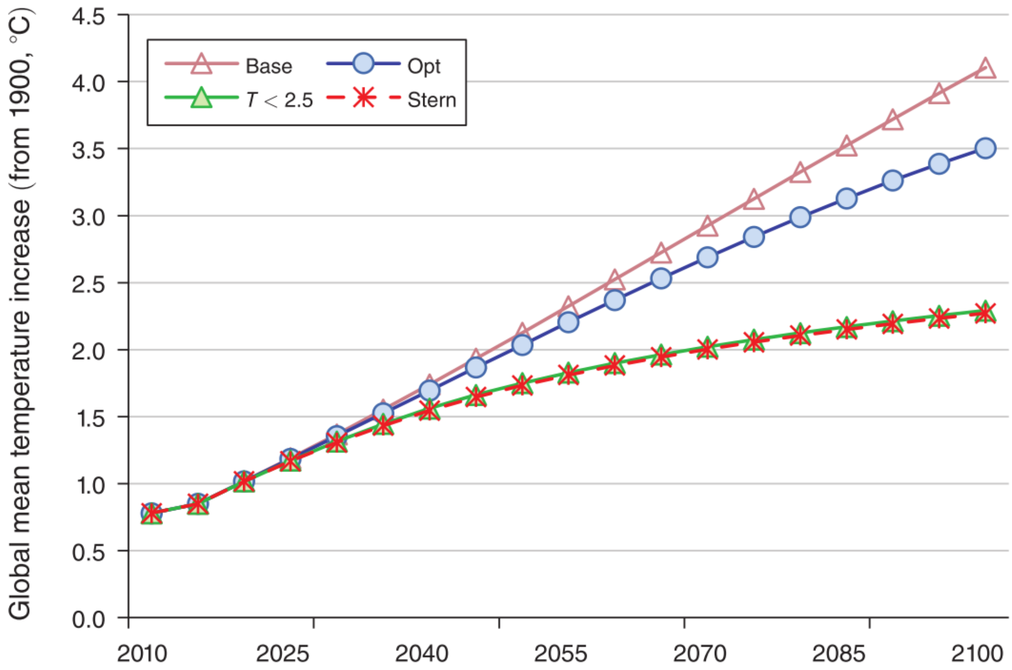
[118] For example, if the SCC are \$50 per tonne of CO_2, then it is optimal to spend a maximum of \$50 per tonne for mitigation. If mitigation is more expensive, it would be better to accept the damage caused by the emission.

[119] We use the term "endogenous" for costs and temperatures derived from CB-IAM. The literature often uses "optimal". We refrain from using such a wording, as it may leave the casual reader under the impression that those costs are a superior or preferable concept. We argue that this is not the case in the context of climate change. The uncertainties of CB-IAM are too substantial to consider the label "optimal" appropriate.

[120] Ironically, Nordhaus is credited by some as the first to mention the 2°C threshold in an early publication on climate change in 1977 (W. D. Nordhaus, 1977). See also https://www.carbonbrief.org/two-degrees-the-history-of-climate-changes-speed-limit (14.01.2020). Yet, in this paper he did not propose 2°C as an upper limit, but merely wrote that "Within a stable climatic regime, such as the current interglacial, a range of variation of 2°C is the normal variation" (ibidem, p. 40). He used this number for a comparison to the estimated range of the climate sensitivity, which he assumed to have a range of 0.6 – 2.9 °C with a best-guess of 2°C as well (ibidem, p. 58). He used this numbers for a first rough estimate of shadow prices of carbon based on mitigation costs.

[121] Nordhaus has recently even been awarded the Nobel Prize for his contribution to CB-IAMs and putting them into use. In his prize lecture, Nordhaus presented on slide 8 an "optimal" SCC of $36\$_{2018}$ per tCO_2 for the year 2015 and an "alternative optimal" SCC (alternative damage function) of 91\$ with an "optimal" temperature increase of 3.5°C or 3°C (alternative), respectively (see https://www.nobelprize.org/uploads/2018/10/nordhaus-slides.pdf; 12.02.2020). Strictly limiting the temperature increase to 1.5°C is "not feasible" in this version of DICE and allowing for overshoots results in a SCC of 236\$.

Figure 23: DICE: Temperature change for different scenarios



Source: Nordhaus, 2018

11 History of damage model development

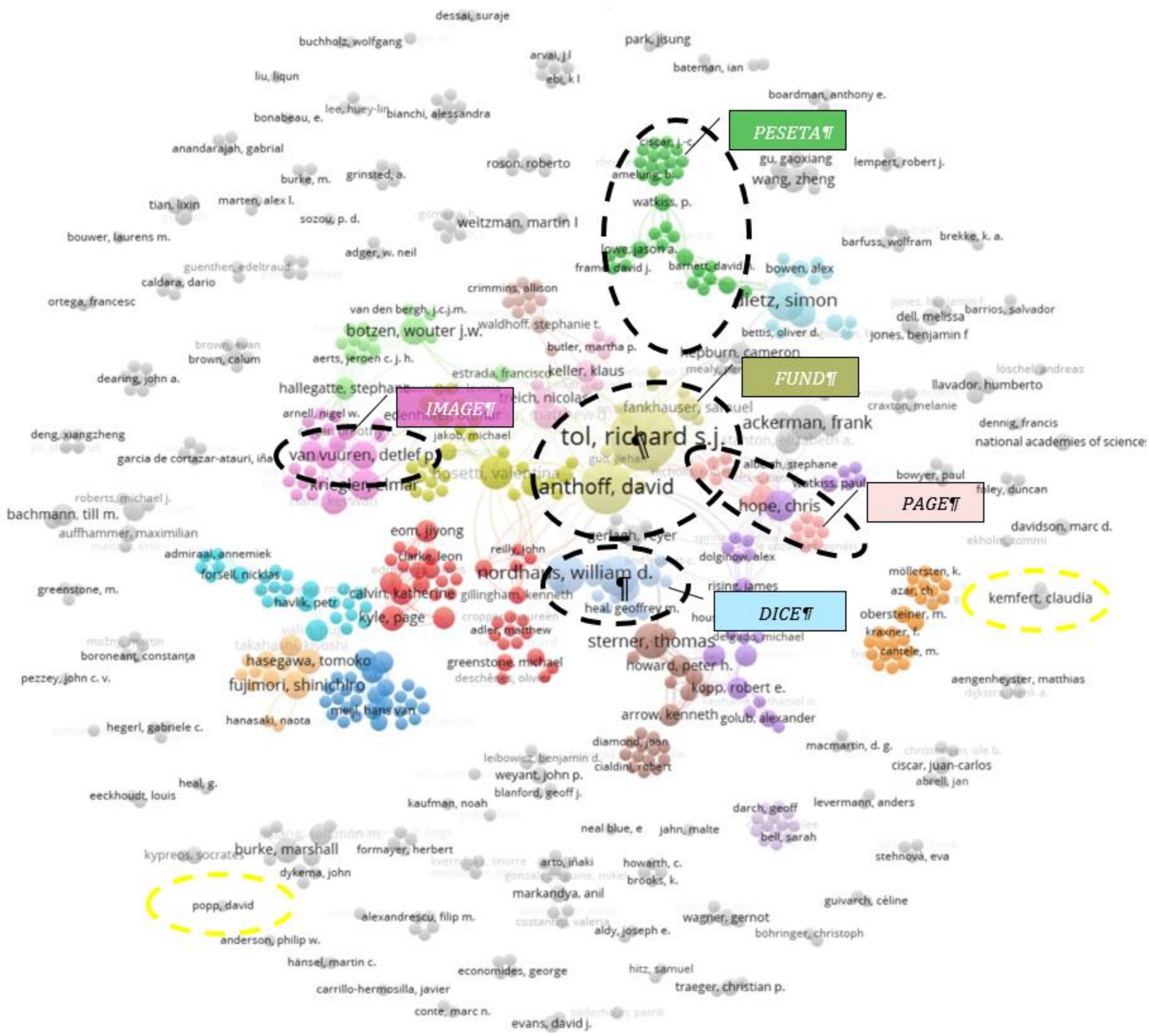
Models that determine the economic consequences of climate change have existed since the mid-1990s (Nordhaus & Yang, 1996). Their number is constantly growing. Some types of damage models of the 1990s are hardly followed up today, while others have been refined and adapted to new findings in climate science or new challenges in climate policy.

The model development is dynamic because of equally dynamic progress in the underlying scientific disciplines. Some of the 1990s models have not survived this dynamic process of change; while new models, on the other hand, are emerging. We are not trying to give a complete account of all existing damage models but only select the most frequently cited or particularly relevant models in the context of this study.

In order to identify the most frequently cited models, we carried out a cluster analysis based on a ZOTERO literature database. Figure 24 shows the interconnection of authors based on the number of studies they published together. It shows that there are small, intensively interwoven groups of authors (black dotted clusters). In addition, models in the EU and Germany (PAGE, WIAGEM) were identified (highlighted in yellow).

In addition, there are numerous individual authors and groups of authors in the periphery (grey satellite cloud) who have devoted themselves to special issues of damage models such as discounting, equity weighting, catastrophic risks, or uncertainty.

Figure 24: Analysis of interconnectedness of authors

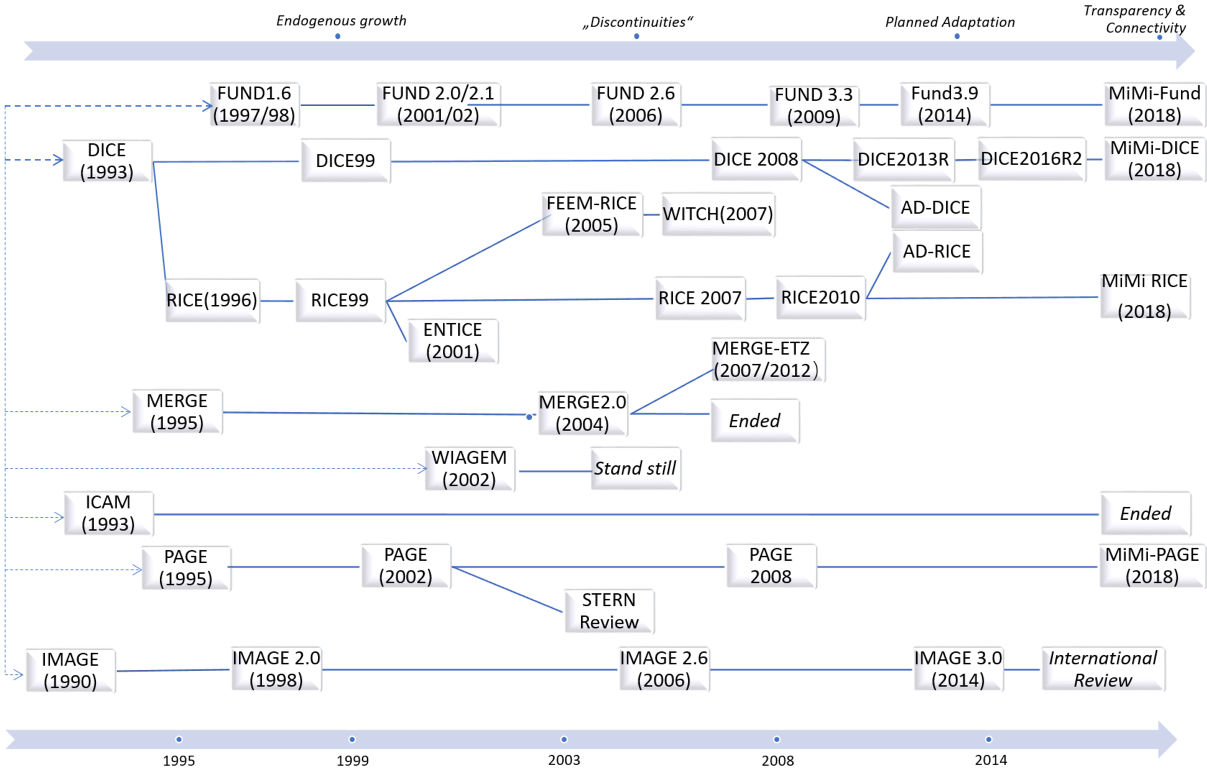


The connections are based on the number of studies the authors published together. We chose the "fractional counting" method, which means that a study published by the same authors counts proportionally less if other authors have been involved as well.

Source: Prof. Dr. Reimund Schwarze, Kleinmachnow, using VOSviewer

This cluster analysis and more in-depth research led us to the damage model genealogy ("family tree") shown in Figure 25.

Figure 25: Family tree of models related to damage costs



Source: Prof. Dr. Reimund Schwarze, Kleinmachnow

Beginning with the CB-IAMs (FUND, DICE with spin-off developments, and MERGE), German and international models are fanned out to detailed process-based damage models (IMAGE) and are reproduced over time with spin-off developments. Others, like ICAM, have not been developed further. The development of CB-IAMs and process-based damage models started simultaneously in the USA and in Europe in the 1990s (DICE, ICAM, IMAGE).

Retrospectively, the "Dynamic Integrated Model of Climate and the Economy" (**DICE**) can be described as a pioneering work. Nordhaus was awarded the Nobel Memorial Prize in Economic Sciences in 2018 for his achievements in the integration of climate change into macroeconomic analysis (including developing DICE). DICE is until today one of the most widely used damage models in academia because it has been open-source for research since its introduction, while competing, more complex bio-physical models such as IMAGE only strive to achieve this wide spread re-use in the context of current quality assurance processes. Transparency thus proves to be a key driver for dynamic model development, the spreading of a framework and development of an entire family of similar models. The series of "descendants" of DICE includes, among other, RICE (W. D. Nordhaus & Yang, 1996), ENTICE-BR (D. Popp, 2006, p. 2006), FEEM-RICE (Bosetti et al., 2009).

FUND ("Climate Framework for Uncertainty, Negotiation and Distribution") was chiefly developed by Richard Tol (Tol, 1997) and is now co-developed with David Anthoff. Some new functionalities such as trade and coalition building (FUND 2.0/FUND 2.1), a longer time horizon (FUND 2.6) and diversified ecosystem impacts and extreme events (FUND 3.3) have been included. The last updated full version is FUND3.9 (Anthoff & Tol, 2014), which will be described in detail in Section12.2.

The **MERGE** (“A Model for Evaluating the Regional and Global Effects of GHG Reduction Policies“) by Alan Manne (A. Manne et al., 1995)is a “fully-integrated energy-economy-climate modelling framework"(Ortiz & Markandya, 2009). It is designed to examine aspects such as, for example, the abatement costs and benefits of mitigation policies, or the effects of discounting. In various respects, MERGE is similar to the original DICE model in its basic structure, both in the core climate-economic model (Global 2200) and in its damage model. MERGE maximizes welfare as the sum of the discounted benefits of current and future consumption and is therefore to be classified as a CB-IAM. It may also be operated in a "cost-effective" mode by fixing a certain climate target. In the course of efforts to endogenize technical progress, which started in the early 2000s, the MERGE model was extended to include algorithms of technological learning such as learning-by-doing (LbD) and learning-by-researching (R&D), which ultimately led to the MERGE-endogenous technology learning (MERGE-ETL)-model (Kypreos, 2007). A further change that was introduced by MERGE-ETL is the economic consideration of geoengineering strategies such as carbon capture and storage (CCS) and afforestation (CDR).

WIAGEM ("World Integrated Assessment General Equilibrium Model") is the only German model in this pool. It was developed by Claudia Kemfert (Kemfert, 2002)and combines an intertemporal CGE with an energy and climate damage sub-models. Thus, economic aspects are considered in more detail than in the aforementioned CB-IAM. On the other hand, WIAGEM does not consider adaptation as a decision variable. In comparison to other studies, in which significant impacts on production only occur in the long term, WIAGEM already shows strong impacts of climate change within a shorter time horizon (2050). Some nonconventional model characteristics of WIAGEM as presented in Roson & Tol, 2006 have led to a stand-still in its development since 2007.

Another pioneering integrated assessment model of the 1990s, **ICAM** ("the Integrated Climate Assessment Model"), has been developed by Hadi Dowlatabadi and Granger Morgan at Carnegie Mellon University, Canada (Dowlatabadi & Morgan, 1993). Though not being designed as CB-IAM, it can be seen as a model to evaluate the trade-off-effects of policies much in the spirit of a CB-IAM. After two decades of work on ICAM, the model developers have stopped further development for two reasons: First, it was not possible to generate consistent trajectories within the model that correspond to those of the Intergovernmental Panel on Climate Change. Second, the authors feared that quantitative results from IAMs such as ICAM would be used "without a proper discussion of the major uncertainties" (Morgan et al., 2017).

The Policy Analysis for the Greenhouse Effect (**PAGE**) model was developed in the early 1990s by Chris Hope, John Anderson and Paul Wenman (Hope et al., 1993) for the economic assessment of the European Commission's climate policy. The most prominent application of the PAGE model is found in the Stern Review (Stern, 2007). It is the first structurally stochastic IAM that uses a set of simplified parametric formulas to map the complex ecological and economic uncertainty. Essentially, all parameters are backed by simple triangular probability distributions. PAGE also considers, for the first time in IAM development, potentially catastrophic effects as so-called "discontinuities". It assumes that the probability of a discontinuity increases with a temperature above a certain threshold. This threshold cannot be influenced by adaptation. *Before* reaching the "discontinuity point", adaptation has a strong effect in the PAGE model, however. It is assumed, for example, that all regions will be able to mitigate 25 percent of non-economic impacts through adaptation (Hope, 2006). De Bruin, 2009 points out that this high effectiveness of climate adaptation in the PAGE model could be overly optimistic in the light of recent empirical findings (de Bruin et al., 2009, p. 66)For a more detailed description of PAGE see Section 12.3.

PAGE, DICE/RICE, FUND and other IAMs[122] have been implemented in the Mimi framework[123] since 2018 to improve the transparency and connectivity of IAMs. The Mimi framework offers orientation in the sprawling model-landscape as it only includes those models that are still actively discussed and developed. Hence, the ICAM, WIAGEM, and MERGE models are not part of the Mimi framework.

IMAGE ("The Integrated Model to Assess the Greenhouse Effect") of the Netherlands Environmental Assessment Agency (PBL; formerly: RIVM/Alcamo Group) belongs to the group of pioneering IAMs. For an introduction and overview, see Alcamo et al., 1995. IMAGE had a lasting impact on the work of the IPCC in the 1990s and 2000s and it was instrumental in defining and analysing the SRES emission scenarios. It is a descriptive, i.e. non-normative, numerical simulation model for the impact assessment of mitigation and adaptation policies on a global scale. Within the group of IAMs, IMAGE is characterized by a relatively detailed mapping of biophysical processes and the consideration of a broad spectrum of environmental influences (e.g. water and nutrient balances), approaching the complexity of a full-fledged earth system model. IMAGE also contains an economic module for the representation of agricultural production and a techno-economic module for the analysis of the energy system. The economic module is less detailed compared to DICE/RICE or FUND, whereas the energy market model is less detailed than typical mitigation-IAMs (e.g. WITCH).

One of the fundamental conflicting objectives in IAMs is "detail versus simplification". Sufficient detail is needed to include all relevant processes of our social and natural systems. Simplicity, on the other hand, is needed to ensure transparency in complex model systems for decision makers and democratic control bodies. As a model framework, IMAGE is seen by some economists as too difficult to communicate with decision makers; many authors regard it as a "black box" compared to the simpler damage or mitigation models (Böhringer & Rutherford, 2008).

FUND, DICE and PAGE are the IAM most frequently used to calculate the SCC. Often, exogenous emission scenarios have been used as inputs such that the mitigation cost part of the IAM could be turned off. Other IAM focus more on cost-benefit analysis. There, only few results on SCC exist.

To sum up, there exist several IAM to calculate climate damages. Depending on the complexity of the environmental policy challenges dealt with, they range from complex biophysical models with isolated economic modules (IMAGE) to highly simplified IAMs that are easily accessible and transparent for the academic community (DICE/RICE). The latter approach led to a dynamic genealogy of IAM. Simple IAM allowed to respond to economic challenges such as endogenous growth, planned adaptation, catastrophic events, and tipping points ("discontinuities") with outsourced model developments ("spin-offs"). Detailed process-modelling versus simplification is a fundamental trade-off in all IAM. The provision of modularized software versions on open access platforms — such as the Mimi framework — improves transparency and accessibility and seems to be an important milestone on the path to further progress in IAM development.

[122] There is an ongoing effort to include more models.

[123] https://www.mimiframework.org/ (20.12.2019)

12 Details of three prominent damage models

In the following we will give an overview over Richard Tol's FUND, Chris Hope's PAGE, and William Nordhaus' DICE, which are the most widely applied and commonly cited IAM in the literature. There exist several versions of each and FUND and DICE are both open source such that, especially for DICE, various extensions and modifications from other authors exist. The following descriptions refer to the current version as designed by the original developers and as implemented in the Mimi framework.[124] For a comprehensive comparison of these three models see also e.g. Rose, 2014 or IAWG, 2016. Some extensions and modifications by the original developers as well as by many other researchers are discussed in Section 13.2.

12.1 DICE

12.1.1 Overview

The "Dynamic Integrated model of Climate and the Economy" (DICE) has been developed in the early 1990s by William Nordhaus. DICE is open source[125] and one of the most widely used damage models. The following description is for Version DICE2013R, based on (W. Nordhaus & Sztorc, 2013). As discussed above, DICE has spanned a model family with a number of descendants, including RICE (W. D. Nordhaus & Yang, 1996), ENTICE-BR (D. Popp, 2006), FEEM-RICE (Bosetti et al., 2009)) and WITCH (Bosetti et al., 2006). See also the model family tree in Section 11.

DICE is a standard neoclassical growth model, which optimizes the consumption path using a social welfare function. It optimizes on the one hand with respect to the savings rate for capital accumulation and on the other hand with respect to an emission control rate μ, which induces mitigation costs but reduces emissions. Output (i.e. GDP) is generated by an isoelastic Cobb-Douglas function with the input factors capital, labour, and technology. Carbon dioxide emissions are endogenously determined by global output, using a time-varying emissions intensity.

DICE combines countries into a global aggregate with a single level of consumption, technology, capital, and emissions. Global aggregates are estimated based on data of twelve regions, using purchasing power parity exchange rates. There is a version of DICE which explicitly models regions instead of aggregating them into one global model. This version is called RICE model (Regional Integrated Climate-Economy).

Consumption "should be interpreted as 'generalized consumption', which includes not only traditional market goods and services like food and shelter, but also non-market items such as leisure, health status, and environmental services" (W. Nordhaus & Sztorc, 2013, p. 6). Changes in population, the labour force, economy-wide technology (which partly determines GDP-growth) as well as carbon-saving technology (which determines mitigation costs) are exogenous.

12.1.2 Climate

The CO_2 emissions accumulate in the atmosphere based on a multi-box carbon cycle model. CO_2 emissions (or strictly speaking the radiative forcing) from land use changes, emissions from

[124] https://www.mimiframework.org/ (20.12.2019)

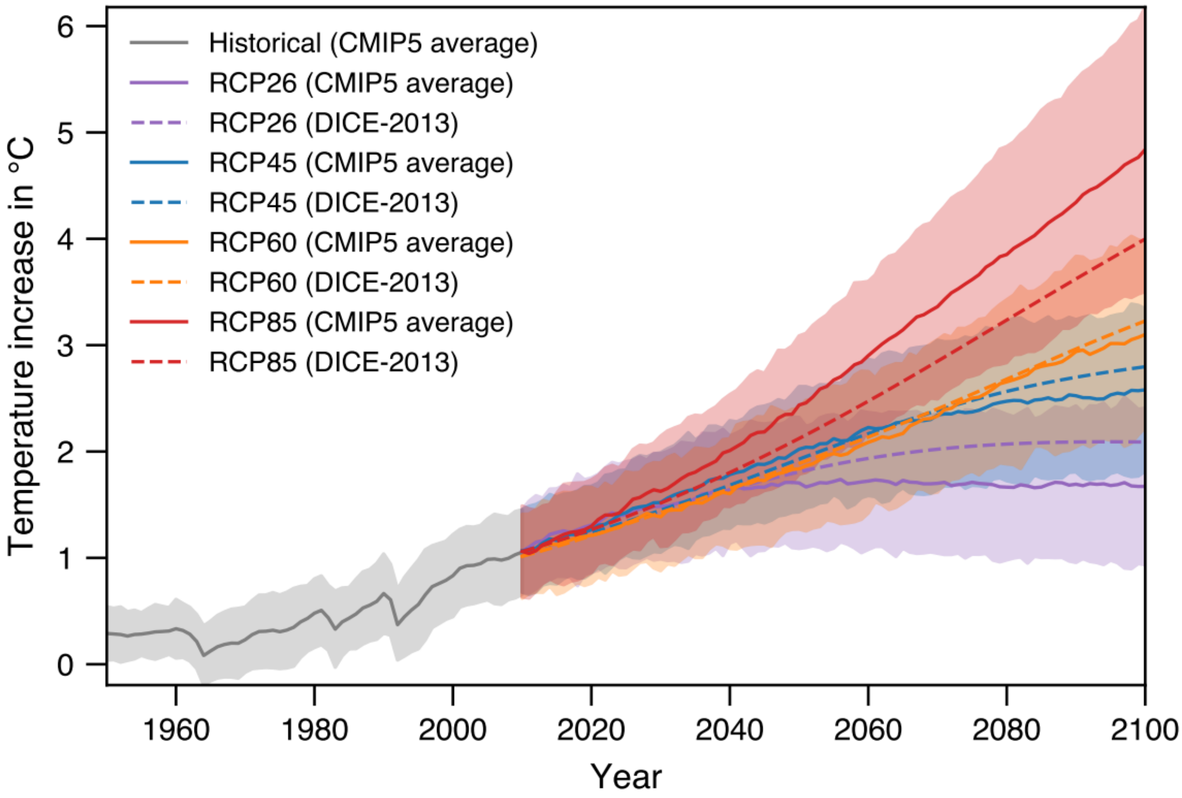
[125] The DICE-code is accessible at https://sites.google.com/site/williamdnordhaus/dice-rice (20.06.2019).

A modular modelling framework (Mimi) version of DICE is available at https://www.mimiframework.org/ (20.06.2019).

other greenhouse gases and aerosols enter the model exogenously according to the RCP 6.0 W/m^2 scenario (see Section 2.4). The radiative forcing of greenhouse gases in the atmosphere lead to an increase in atmospheric temperature. This increase occurs with a certain time lag, which is modelled using a two-box model that considers the atmosphere and the lower ocean. The equilibrium temperature sensitivity corresponds to the temperature increase if a steady state is reached (i.e. if the greenhouse gas concentrations are constant and temperature changes of the lower ocean and the atmosphere have reached the same value).

Figure 26 shows that DICE-2013 projects lower temperature increases than the CMIP5 ensemble of global circulation models that has been used for the IPCC AR5 report.

Figure 26: Temperature projected by DICE-2013 and the model ensemble used in IPCC AR5



Temperature development projected by DICE-2013 (dashed curves) and by the CMIP5 model ensemble used in IPCC's AR5 (IPCC, 2013). Solid lines represent average of the CMIP5 ensemble, shadings show the 1.64 standard deviation range. For the DICE-2013, temperature development RCP-equivalent emission data has been used to run the carbon cycle and climate module.

Source: Glanemann et al., 2020, Figure S7.

12.1.3 Mitigation

CO2-emissions arise from economic output as follows:

$$\mathrm{CO_2} - \mathrm{Emissions}(t) = GDP(t) * \sigma(t) * \left(1 - \mu(t)\right)$$

With

- GDP(t): Level of output at time t;
- σ(t): carbon intensity (emissions per GDP);
- μ(t): emission control rate at time t;

The emission control rate causes mitigation costs according to the following function:

$$\text{Mitigation Costs}(t) = GDP(t) * \theta_1(t) * \mu(t)^{\theta_2}$$

where $\theta_1(t)$ and θ_2 are parameters. The costs of emission reductions are calibrated to the EMF-22 report[126]. DICE Version 2013 includes a backstop technology, which is a technology that can replace all fossil fuels at a high price. In this case it is \$344 per ton CO_2 (2005 prices) in 2010 and it declines at 0.5% per year due to technological progress.

12.1.4 Damage

The DICE model Version 2013 does not differentiate between sectors. This is a change from earlier model versions, which did include several sectors. Nordhaus (W. Nordhaus & Sztorc, 2013) argues that this is because sectoral estimates were increasingly outdated and unreliable and because complex models increase the risk of coding errors as e.g. in FUND version 3.5 (see also Ackerman & Munitz, 2012). Thus, the damage function was greatly simplified and lumps together all sectors (including sea-level rise). It is a polynomial function of atmospheric temperature change and assumes that damages are proportional to world GDP:[127]

$$\text{Damages }(t) = GDP(t) * (\psi_1 * \Delta T(t) + \psi_2 * \Delta T(t)^2)$$

With:

- Damages(t): Climate damages as a fraction of GDP at time t;
- GDP(t): Level of output at time t (not accounting for climate damages);
- ψ_1, ψ_2: Shape parameters of the damage function;
- $\Delta T(t)$: Increase in global mean temperatures (in °C);

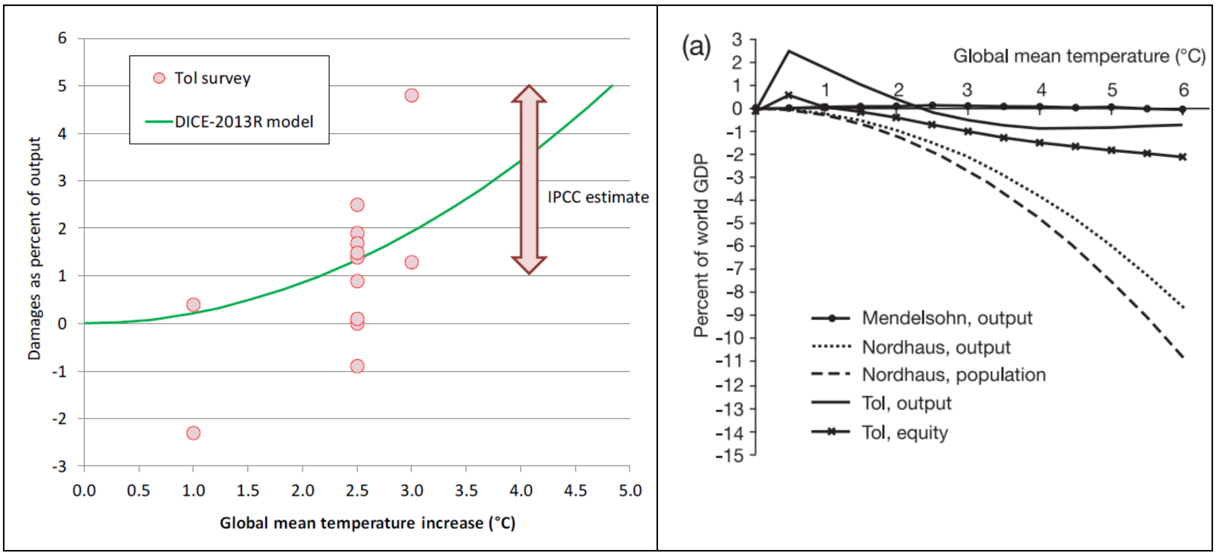
The following Figure 27 (left hand side) shows that DICE's damage function is calibrated according to a survey from Tol, 2009 on model-results and a statement from IPCC AR4 (Yohe et al., 2007) that "global mean losses could be 1–5% GDP for 4°C of warming" (p.17). Yet, this IPCC estimate is in turn based on damage model results (see right hand side of the following figure). Thus, the calibration is entirely based on previous results from DICE itself and other damage models. (W. D. Nordhaus, 2007) conceded that this damage function is "rather weak" in view of the empirical basis on which it rests.

[126] See EMF 22: Climate Change Control Scenarios | Energy Modeling Forum (stanford.edu) Nordhaus &Sztorc, 2013 do not provide any further details as to which of the many results of that report have been used.

[127] We chose the form provided in the modelling appendix (p.100) of Nordhaus & Sztorc, 2013. Surprisingly, according to Equation (4) of the same document, the damages function is

Damages $(t)=GDP(t)*1/[1+ \psi_1*\Delta T(t) + \psi_2*\Delta T(t)^2]$.

Figure 27: Calibration of DICE's damage function



Source: Left: Nordhaus and Sztorc 2013; Right: Source of "IPCC Estimate" IPCC AR4 (Yohe et al., 2007) Figure 20.3 (where in turn IPCC2001b is referred to as source)

12.2 FUND

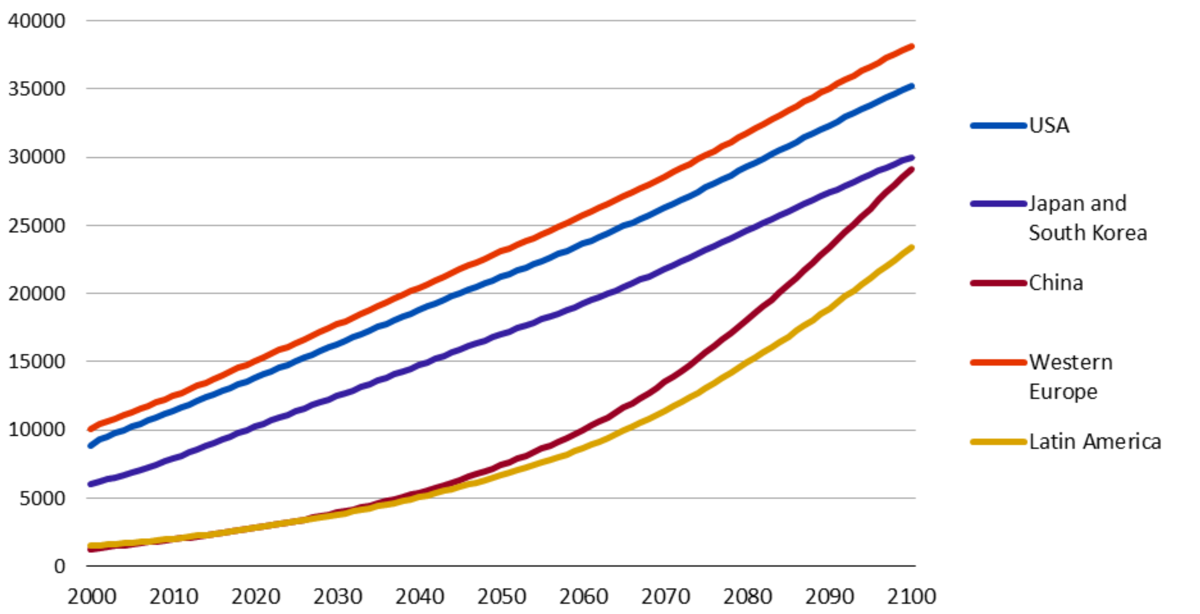
12.2.1 Overview

The FUND model (Climate Framework for Uncertainty, Negotiation and Distribution) was developed by Richard Tol Tol, 1997 and is now co-developed together with David Anthoff. Since its inception, the FUND model has been updated to include some new functionalities such as trade and coalition formation (FUND 2.0/FUND 2.1), a longer time horizon (FUND 2.8) and diversified ecosystem impacts as well as extreme events (FUND 2.8). The latest updated full version is FUND3.9 which is described in the following based on Anthoff & Tol, 2014.

FUND is defined for 16 world regions[128] and distinguishes between 14 impact sectors. It runs from 1950 to 2300 in one-year time steps. Population size and regional GDP follow a special "FUND-scenario" (see Figure 28 and Figure 29 for an overview of the different GDP growth paths). FUND can also be run with SRES-scenarios. Emissions is the only variable that is defined endogenously. The model allows the comparison of mitigation costs with avoided damage in a welfare maximising framework.

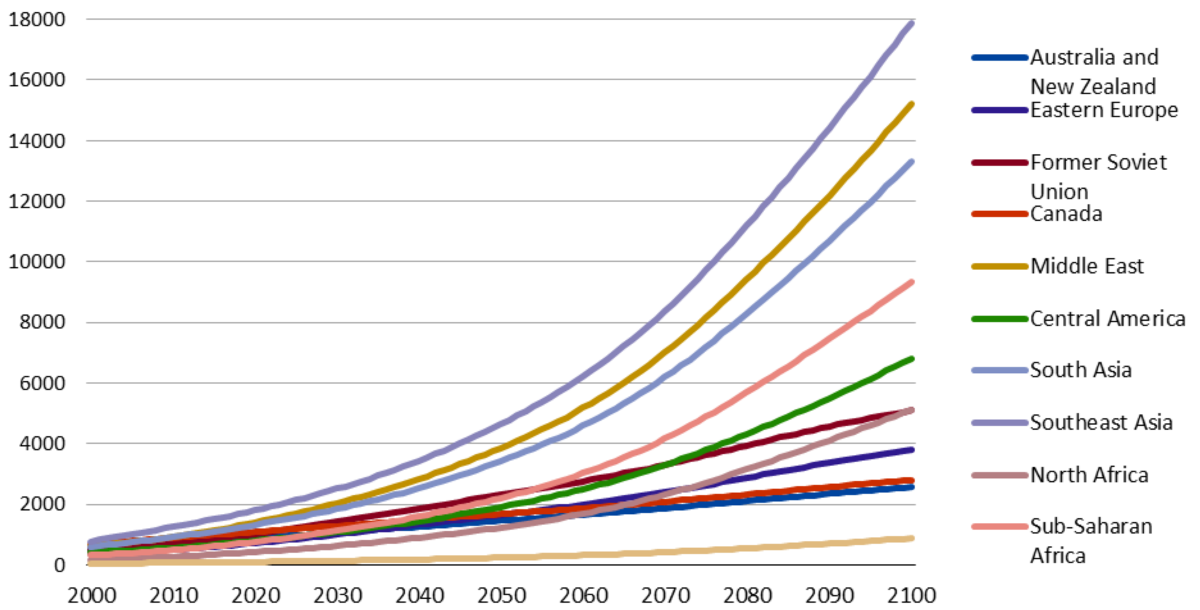
[128] United States of America, Canada, Western Europe, Japan and South Korea, Australia and New Zealand, Central and Eastern Europe, the former Soviet Union, the Middle East, Central America, South America, South Asia, Southeast Asia, China, North Africa, Sub-Saharan Africa, and Small Island States

Figure 28: FUND's Regional GDP — Primary Regions in Billion US$ (1995)



Source: own illustration, Infras based on FUND's Mimi-Version. See https://www.mimiframework.org/ (20.12.2019)

Figure 29: FUND's Regional GDP in FUND — Rest of the World in Billion US$ (1995)



Source: own illustration, Infras based on FUND's Mimi-Version. See https://www.mimiframework.org/ (20.12.2019)

12.2.2 Climate

FUND's climate module is similar to DICE's. Major differences are that FUND explicitly models non-CO_2 GHG, whereas DICE uses their radiative forcing exogenously. In addition, FUND includes a carbon cycle feedback, which takes into account that climate change causes emissions from the terrestrial biosphere (e.g. forest dieback, melting permafrost).

12.2.3 Mitigation

In FUND, emissions are the product of the emission intensity (emission per energy use), energy intensity (energy use per GDP), and GDP ($), also known as the Kaya Identity. Emissions thus increase with GDP, while they decrease with efficiency improvements related to both intensity types.[129] Those improvements occur exogenously (i.e. at a fixed pace). In addition, efficiency improves with a variable τ that represents costly policies. τ is FUND's endogenous variable that allows to set the mitigation effort (in this case indirectly). The efficiency improvements triggered by the policy fade out after the policy is stopped. Yet, a certain improvement level remains permanently (under the assumption that the policy induces technological lock-in effects).

The mitigation costs are dependent on policy level τ based on a quadratic relationship Mitigation costs decrease with the regional and global knowledge stock and are, ceteris paribus, higher in regions with low emission levels (FUND assumes that those regions have already implemented less costly mitigation measures, i.e. have fewer "low-hanging fruits" left to reap). The knowledge stock increases with each policy, such that the mitigation costs decrease for a given policy.

The mitigation costs are calibrated such that a 10% emission reduction in 2003 costs 1.57% (1.38%) GDP in the least (most) carbon-intensive region (calibrated according to Hourcade et al., 1996 and Hourcade et al., 2001). An emission reduction of 80% (85%) would reduce GDP by 100%. This calibration is not realistic. The reductions implied by the Paris Agreement are higher but estimates on mitigation cost are far lower (see Part 3 Mitigation Costs).

12.2.4 Damage — overview

FUND models the impact in the following 14 sectors: sea level rise, agriculture, forests, heating, cooling, water resources, tropical storms, extratropical storms, biodiversity, cardiovascular respiratory, vector borne diseases, morbidity, diarrhea, migration.[130]

In a nutshell, there are two types of damages: damages that relate to a region's GDP (e.g. energy consumption, forestry, water resources) and damages that relate to the population size (e.g. human health or ecosystem). Damages are based on sector-specific functions (each including temperature and sector-specific parameters) and are calibrated for an impact of 1°C warming (or a temperature change of 0.04°C per year).[131]

Human health related sectors, for example, calculate premature deaths or an increase in morbidity. These effects are subsequently monetized, using the value of a statistical life or of a year of morbidity. Statistical life is set to be 200 times the annual per capita income, each year of morbidity is valued at 0.8 times the annual per capita income.

Impact may have negative effects (e.g. increased need for cooling or deterioration of ecosystems) or positive effects (e.g. reduced need for heating or CO_2 fertilization in agriculture). Climate adaptation occurs in two sectors. For sea level rise, decision-makers decide based on the net present value of the adaptation measure (e.g. coastal protection). Thus, adaption and its cost are explicitly accounted for. In the agricultural sector, parts of the damage stem from the rate of climate change, such that damages are lower if temperature increases less rapidly. Hence, adaptation is implicitly assumed in the process, but does not entail any cost in the model.

[129] Forestry measures are not possible and there is no backstop technology.

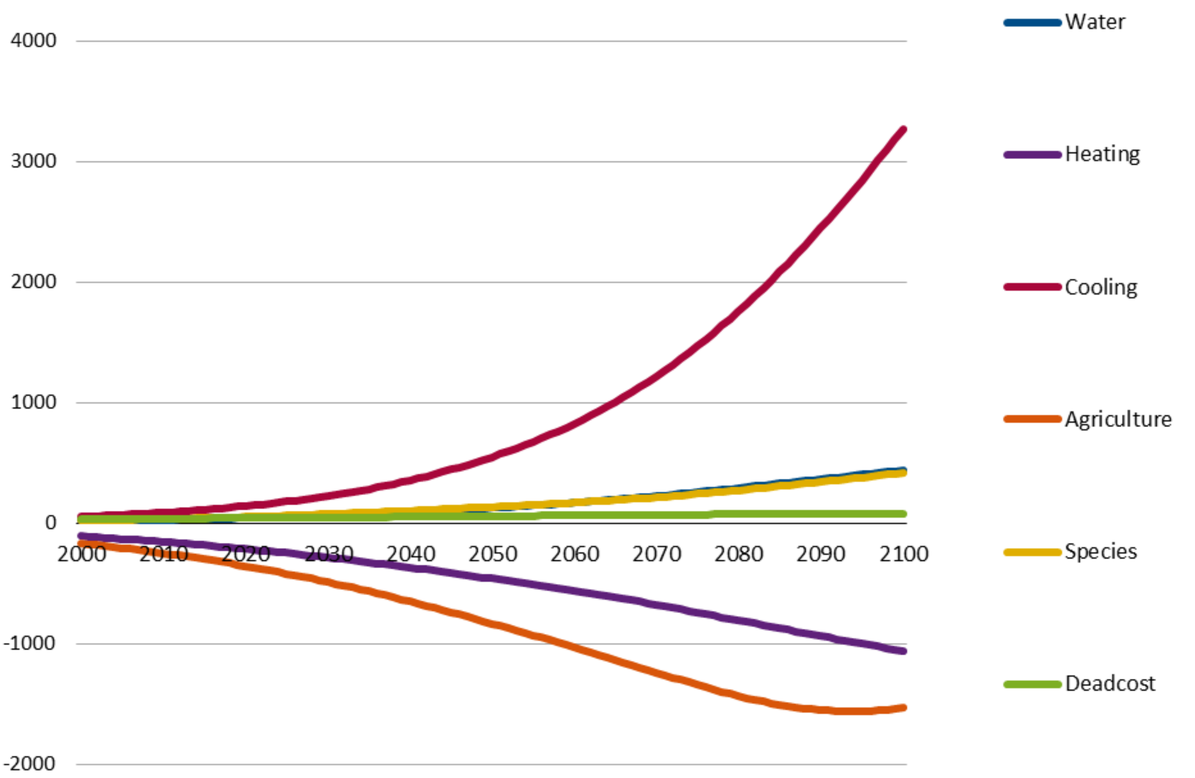
[130] Note that several of these sectors are, e.g., related to human health, which could be seen as a single sector.

[131] The calibration of the impact sectors has not been updated significantly since Tol, 1997 and hence hardly reflects new findings.

The following figures show the damages as given in FUND's Mimi-Version.[132] The figures differentiate between six primary impact sectors where damages are much larger than for the 8 other sectors. In addition, the figures depict the damages as a share of the current GDP (that is the GDP at the respective time).

Even though damages seem high in absolute numbers in FUND (Figure 30 and Figure 31), relative to overall GDP they are insignificant (Figure 32and Figure 33). By far the most important sectors are cooling, heating and agriculture. Cooling is the only sector where costs increase steeply. As we show later, costs stem mainly from one region — China. The heating and agriculture sectors benefit from climate change. Note that cooling is strictly speaking an adaption cost. The respective benefits (e.g. a decrease in heat related death or higher productivity) are reflected in FUND.

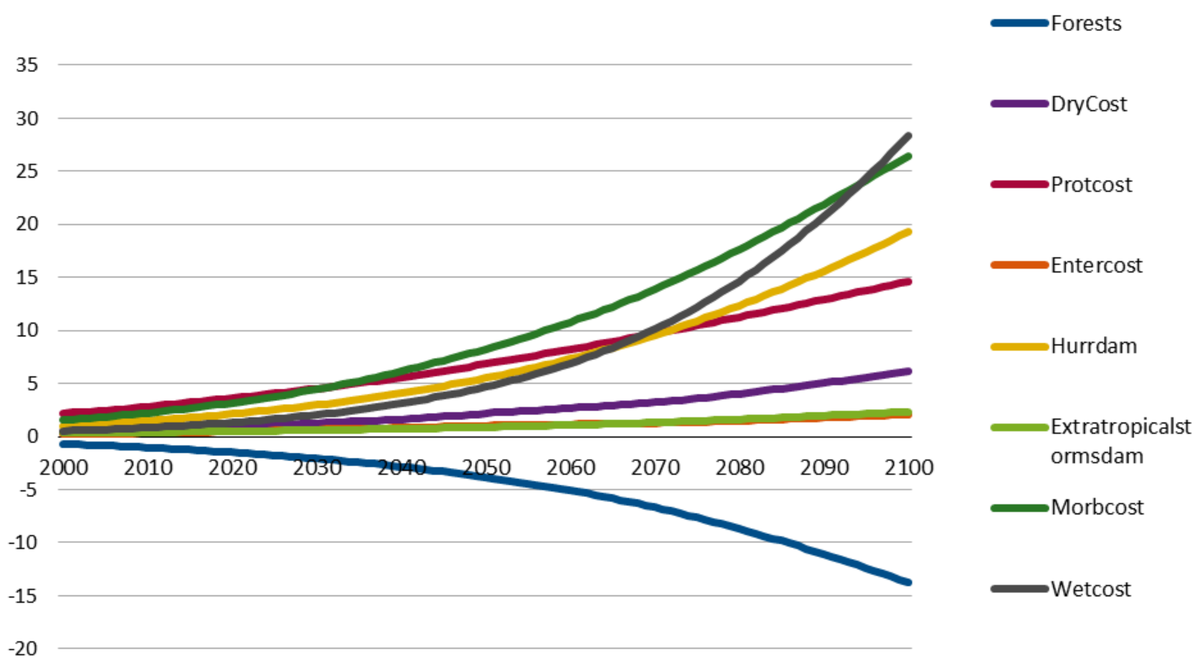
Figure 30: FUND's Damages — Primary Sectors in Billion US$ (1995)



Source: own illustration, Infras based on FUND's Mimi-Version. See https://www.mimiframework.org/ (20.12.2019)

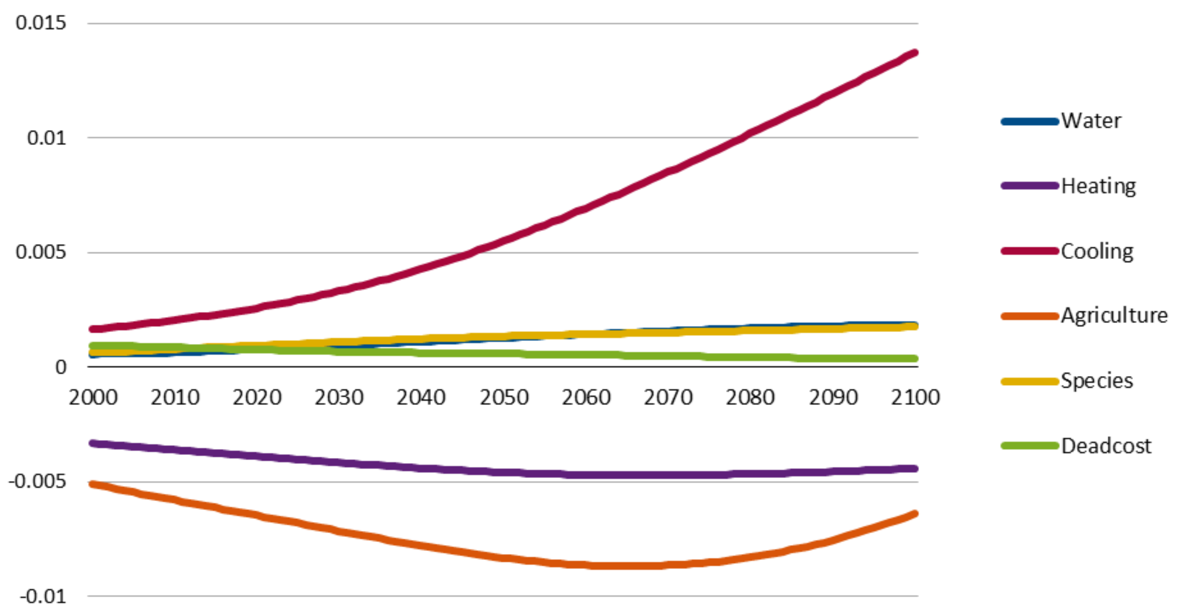
[132] Note that in the present study, damaging effects have positive values and beneficial effects have negative values.

Figure 31: FUND's Damage — Further Sectors in Billion US$ (1995)



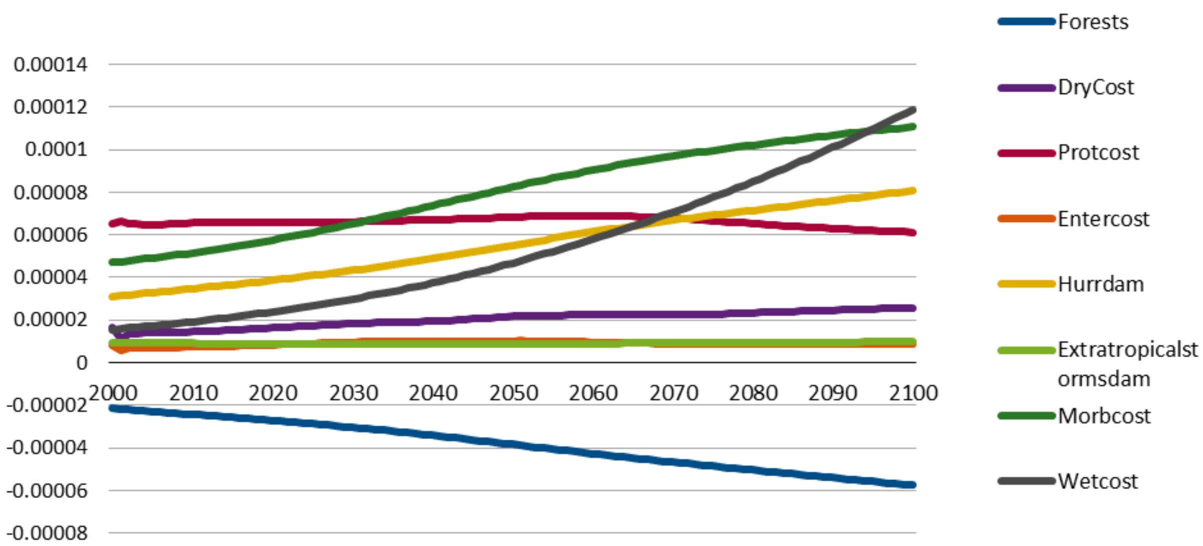
Source: own illustration, Infras based on FUND's Mimi-Version. See https://www.mimiframework.org/ (20.12.2019)

Figure 32: FUND's Damage — Primary Sectors as share of current GDP



Source: own illustration, Infras based on FUND's Mimi-Version. See https://www.mimiframework.org/ (20.12.2019)

Figure 33: FUND's Damage — Further Sectors as share of current GDP



Source: own illustration, Infras based on FUND's Mimi-Version. See https://www.mimiframework.org/ (20.12.2019)

12.2.5 Damage — sector details

To get a better understanding of FUND, in the following we will provide a more detailed analysis of formulas and results of the sectors cooling and agriculture (FUND's two most relevant impact categories) as well as sea-level rise. This Section is targeted to mathematically inclined readers and includes several equations.

12.2.5.1 Cooling

The impact of cooling results from an increase in energy consumption and is modelled as follows:

$$SC_{t,r} = \alpha_r Y_{t=1990,r} \left(\frac{T_t}{1.0}\right)^{\beta} \left(\frac{Y_{t,r}}{Y_{t=1990,r}}\right)^{\varepsilon} \left(\frac{P_{t,r}}{P_{t=1990,r}}\right) / \prod_{s=1990}^{t} AEEI_{s,r}$$

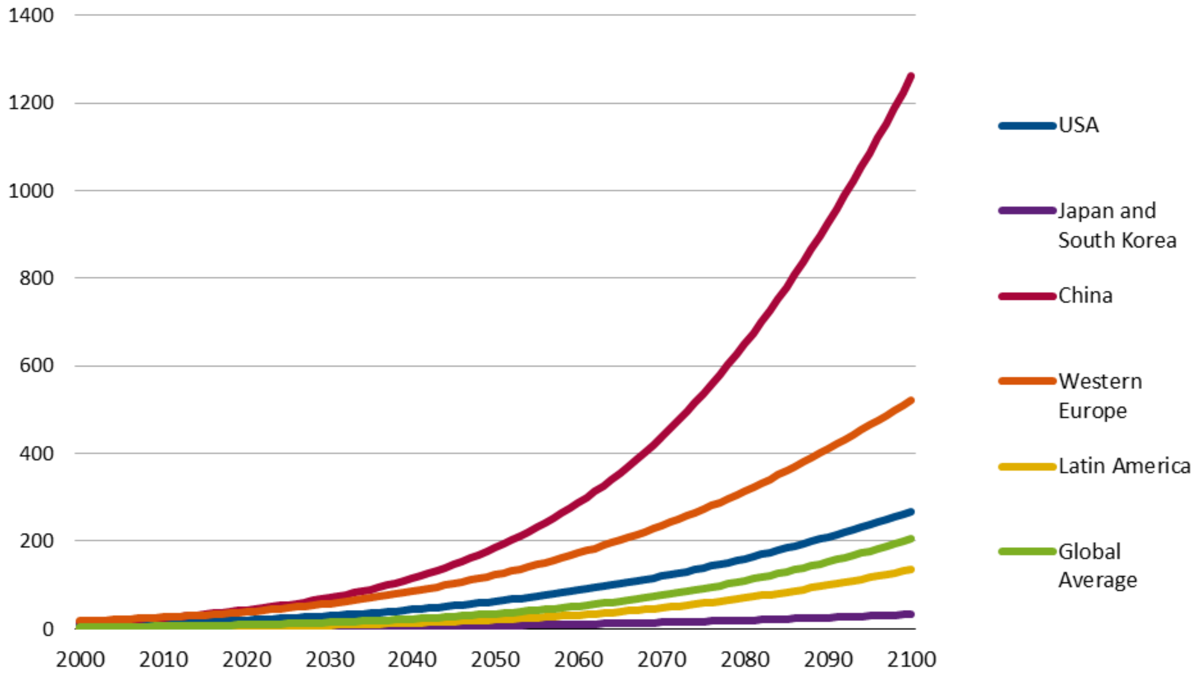
where

- $SC_{t,r}$ represents expeses of space cooling (1995 US$) at time t in region r;
- t represents time;
- r represents region;
- α_r is a regional parameter;
- $y_{t,r}$ is per capita income per year (in 1995 US$) at time t in region r;
- $Y_{t,r}$ is income per year (in 1995 US$) at time t in region r;
- T_t represents the change in the global mean temperature in relation to 1990 (in degree Celsius) at time t;
- β is a parameter; β = 1.5 (1.0-2.0);
- $P_{t,r}$ represents population size at time t in region r;

- ε is a parameter representing the income elasticity of space heating demand; ε = 0.8;
- AEEI is a parameter representing autonomous energy efficiency improvement, which measures technological progress in energy provision; the global average value is about 1% per year in 1990 and is expected to converge to 0.2% in 2200.

Basically, the loss increases *non-linearly* with temperature and income as these both increase cooling demand, while increasing *linearly* with population growth. The income elasticity of cooling demand is taken from Hodgson & Miller, 1995 (cited in Downing et al., 1996[133])which are estimates for the UK. α is the calibration parameter which uses the data from Downing et al., 1996 as benchmark for a 1°C temperature increase. In the US, for example, FUND assumes a 0.212% GDP-loss for an increase of 1°C. In China, FUND assumes a GDP-loss of 2.891%. This is more than ten times the US-value and by far the highest percentage of all regions. Figure 34 shows that, accordingly, cooling costs in China are much higher than the world average. For the year 2100, damages in China due to cooling are 39% of global cooling costs and indeed correspond to 74% of the net total costs of climate change (note that heating and agriculture have negative costs).

Figure 34: FUND's Damages for Sector "Cooling" in various regions in Billion US$ (1995)



Source: own illustration, Infras based on FUND's Mimi-Version. See https://www.mimiframework.org/ (20.12.2019)

12.2.5.2 Agriculture

The impact of climate change on agriculture is calculated as follows:

Step 1: Determine gross agricultural product $GAP_{t,r}$ according to the following formula, where the share of GAP in total GDP decreases as countries grow richer (see Figure 35).

[133] See note at bottom of page on FUND's website: http://www.fund-model.org/publications/ (accessed 26.11.2020)

$$GAP_{t,r} = Y_{t,r} \frac{GAP_{t=1990,r}}{Y_{t=1990,r}} \left(\frac{y_{t,r}}{y_{t=1990,r}} \right)^{\varepsilon}$$

where

- $GAP_{t,r}$ is gross agricultural product (1995 US$) at time t in region r;
- t represents time;
- r represents region;
- $y_{t,r}$ is per capita income per year (in 1995 US$) at time t in region r;
- $Y_{t,r}$ is income per year (in 1995 US$) at time t in region r;
- ε is a parameter; ε = 0.31; it is the income elasticity of the share of agriculture in the economy

Step 2: Calculate impact as a percentage of GAP.

There are three impact components:

1. *Rate* of climate change ($A_{t,r}^{Rate}$): This impact is always negative, as "farmers have imperfect foresight and are locked into production practices, climate change implies that farmers are maladapted. Faster climate change means greater damages" (Anthoff & Tol, 2014). For example, a rate of change of 0.04°C per year decreases the production by 0.021% in the US or by 0.013% in China. Those damages fade away according to an exogenously set parameter, reflecting adaptation. This adaption occurs at no cost and is thus implicit. This component is of minor relevance compared to the following two (see Figure 36).
2. *Level* of climate change ($A_{t,r}^{Level}$): This impact can be positive or negative, "as there is an optimal climate for agriculture. If climate change moves a region closer to (away from) the optimum, impacts are positive (negative); and impacts are smaller nearer to the optimum" (Anthoff & Tol, 2014, p. 5). FUND uses a quadratic function with respect to temperature change. The parameters are calibrated for a change of 3.2°C against pre-industrial levels. Figure 37 shows that climate change is beneficial for low temperature ranges and gets problematic only for higher values (depending on the current climate of the region).
3. CO_2 fertilization ($A_{t,r}^{CO_2-fertilization}$) is always positive, as an elevated CO_2-level enhances plant growth and decreases water requirements. This is modelled using a logarithmic function. The effect of CO2 fertilization differs considerably among regions (see Figure 38).

The three components are summed up for each region r and each time period t to $A_{t,r}^{Total}$:

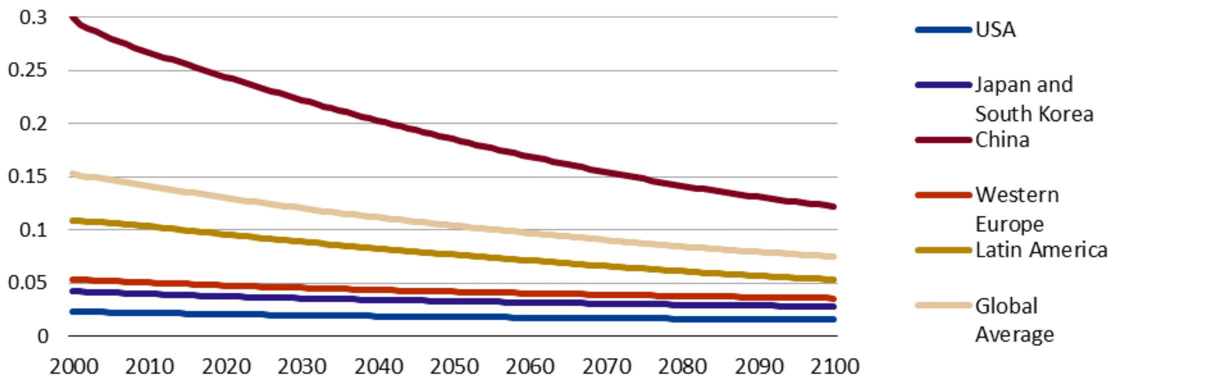
$$A_{t,r}^{Total} = A_{t,r}^{Rate} + A_{t,r}^{Level} + A_{t,r}^{CO_2-fertilization}$$

Step 3: Calculate damages.

As a last step, the loss in total agricultural production is translated into monetary terms using GAP.

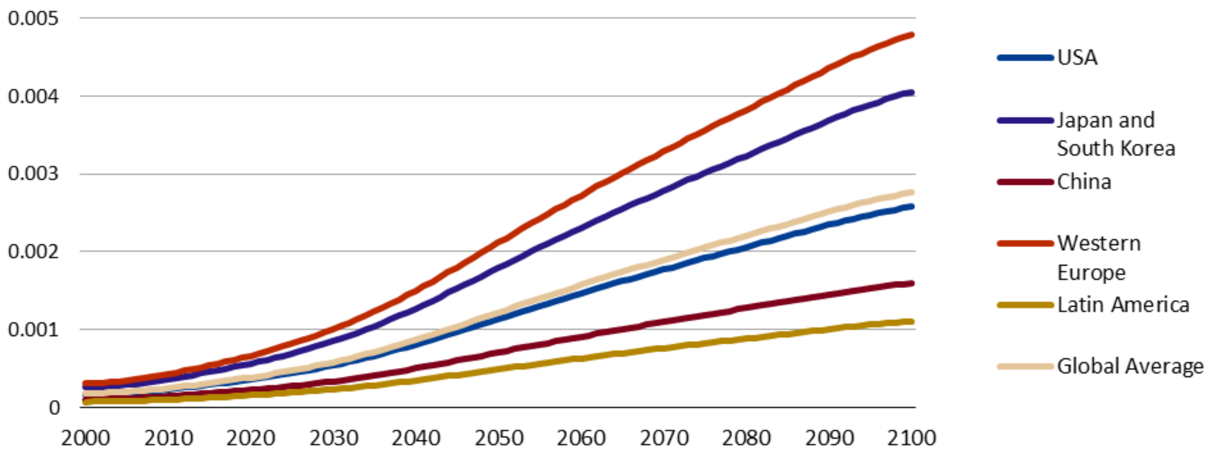
$$D_{t,r}^{Agriculture} = A_{t,r}^{Total} GAP_{t,r}$$

Figure 35: FUND's regional GAP as a fraction of GDP



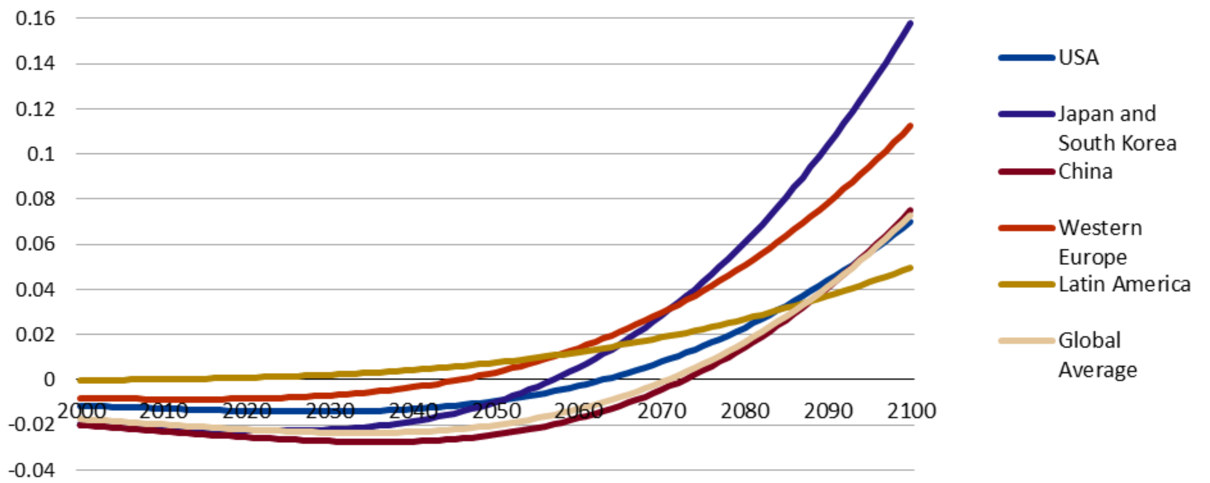
Source: own illustration, Infras based on FUND's Mimi-Version. See https://www.mimiframework.org/ (20.12.2019)

Figure 36: FUND's Share of GAP lost due to rate effect (different scale)



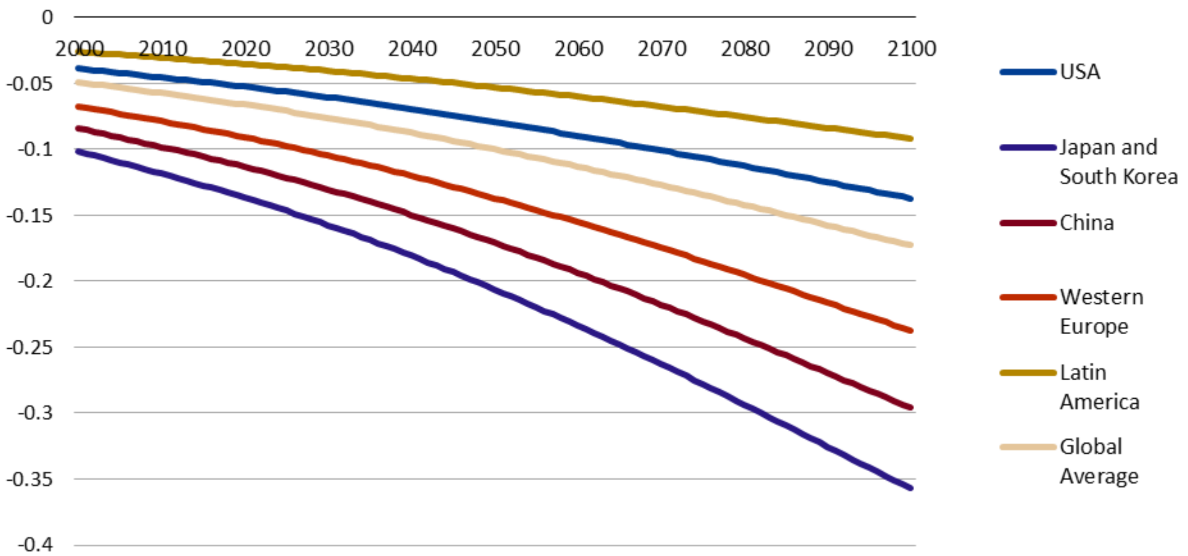
Source: own illustration, Infras based on FUND's Mimi-Version. See https://www.mimiframework.org/ (20.12.2019)

Figure 37: FUND's share of GAP lost due to level effect



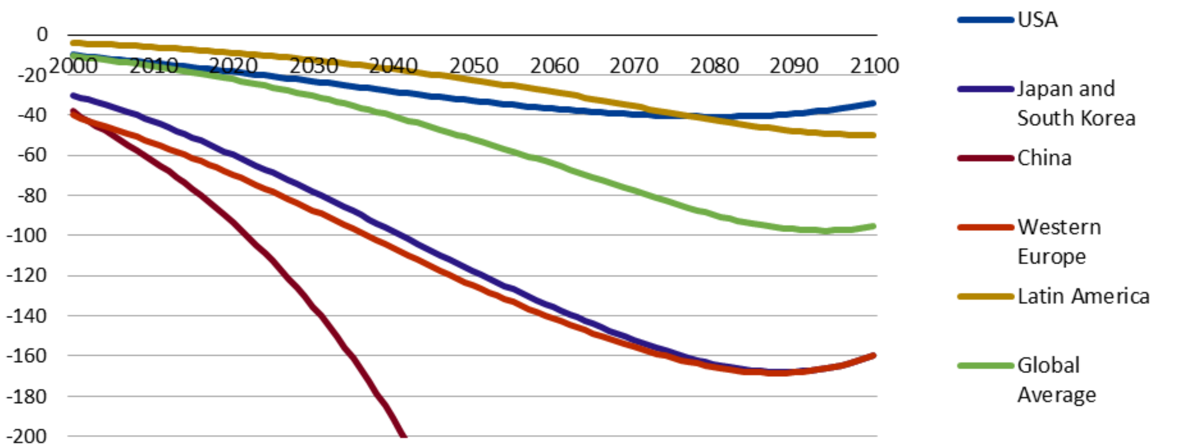
Source: own illustration, Infras based on FUND's Mimi-Version. See https://www.mimiframework.org/ (20.12.2019)

Figure 38: FUND's share of GAP lost due to CO2 fertilization effect



Source: own illustration, Infras based on FUND's Mimi-Version. See https://www.mimiframework.org/ (20.12.2019)

Figure 39: FUND's damage in sector agriculture in Billion US$ (1995)



The Chinese damages decrease to approx. –800 Billion US$ in 2100 (and increase thereafter to approx. –300 Billion US$ in 2150.

Source: own illustration, Infras based on FUND's Mimi-Version. See https://www.mimiframework.org/ (20.12.2019)

The CO_2-fertilization effect dominates the level effect in the 21th century such that, overall, agriculture benefits from climate change (see Figure 39). From 2135 onwards the picture changes and agriculture incurs positive damages (not shown).

FUND's approach is purely focused on temperature and does *not* take into account that agriculture is affected by several other factors such as *changes in precipitation* (annual averages but also seasonal shifts, draughts, etc.), *cold spells* or *pests*.

12.2.5.3 Sea level rise

There are three cost components of sea level rise:

- Loss of dryland and wetland valued per square kilometer lost (both values increase with GDP)

- Forced migration. The cost of emigration is set to be 300% of per capita income of the abandoned region and the value of immigration is 40% of the per capita income in the host region.
- Adaptation cost for coastal protection. The decision is modelled using a cost-benefit analysis.

The set-up of FUND is such that none of these three categories features relevant costs in relative or absolute terms. This is true even for the region "Small Island States". Apparently, this is due to FUNDS's assumption that protection measures are generally effective and affordable.

12.3 PAGE

12.3.1 Overview

The Policy Analysis for the Greenhouse Effect (PAGE) model has been developed in the early 1990s for the economic evaluation of climate policies of the European Commission (Hope et al., 1993). The most prominent application of the PAGE model was in the Stern Review (Stern, 2007).

PAGE includes ten non-constant time-intervals spanning 200 years[134] and divides the world into eight regions.[135] It is a structurally stochastic model that uses a number of simplified parametric formulas to replicate the complex environmental and economic interactions. Essentially, all parameters have a triangular probability distributions and the stochastic features are designed to encompass the uncertainty of the best available knowledge found in the literature, or the randomness of nature itself (Alberth & Hope, 2007). The data ranges are sampled using Latin Hypercube Sampling (Monte Carlo approach). Uncertainty not only affects the linear proportionality factors of functions (as in other damage models) but also parameters that determine the shape of functions (e.g. exponents, curvature parameters). PAGE thus tries to tackle not only parametric uncertainty but to a certain degree also structural uncertainty.

The following description applies to PAGE2009 and follows Hope, 2011.

12.3.2 Climate

To model the carbon cycle, PAGE does not use a box-model but assumes that 60% of CO_2-emissions remain in the atmosphere on a short time scale (best guess; the other 40% are taken up immediately by fast sinks immediately) and 35% of the emissions stay in the atmosphere forever. Between those values, CO_2 reduces asymptotically (best guess: half-life of 73 years). To simulate the decrease in CO_2-absorption on land and in the ocean as temperature rises, there is an additional carbon cycle feedback (best guess: 10% CO_2-concentration increase per °C warming). The additional feedback gain is capped (best guess: 53%), to prevent run-away concentrations in higher emission scenarios.

Furthermore, PAGE does not implement climate sensitivity directly, but derives it from the transient climate response (best guess: 1.7°C) and the feedback response-time of the Earth to a change in radiative forcing. The latter is called the "half-life of global warming" (best guess: 35 years), which result in a modelled climate sensitivity of 2.99°C in PAGE. Triangular distributions for transient climate response and half-life of global warming result in a probability distribution of the climate sensitivity with a long right tail. Regional temperature is adjusted based on three

[134] Analysis years are 2009, 2010, 2020, 2030, 2040, 2050, 2075, 2100, 2150, 2200.

[135] European Union, Eastern Europe and former Soviet Union, China and Central Asia, India and Southeast Asia, Africa and Middle East, Latin America, other OECD.

criteria First, based on the latitude of the region as warming is more pronounced at high latitudes (best guess: pole excess temperature change is 1.5°C compared to equator). Second, based on surface-type (ocean vs. land) of the regions as warming is less pronounced over the oceans (best guess: land excess temperature of 1.4°C compared to ocean). Third, based on local sulphate emissions, which scatter incoming solar radiation and thus exert a cooling effect.

Sea level is modelled *explicitly* as a lagged linear function of global mean temperature.

12.3.3 Mitigation

Marginal abatement costs (MAC) for each GHG and in each region are represented by a continuous marginal abatement curve. Abatement costs are the costs associated with emission reductions as compared to a business-as-usual path. The curve is specified by three points and by two parameters. The three points are: 1) the (possibly negative) marginal abatement cost of the first unit of abatement, 2) the proportion of business-as-usual emissions that can be abated at negative costs, and 3) the end-point of the curve (a high level of mitigation where the marginal abatement costs are very high). The two parameters describe the curvature of the MAC curve for A) negative and for B) positive costs, respectively.

Technical progress is represented by introducing annual proportional growth rates of points 1) and 2), which changes the shape of the curve over time. There is autonomous technological progress, as well as learning-by-doing, by applying an experience curve that is linked to the cumulative CO2 abatement (Alberth & Hope, 2007).

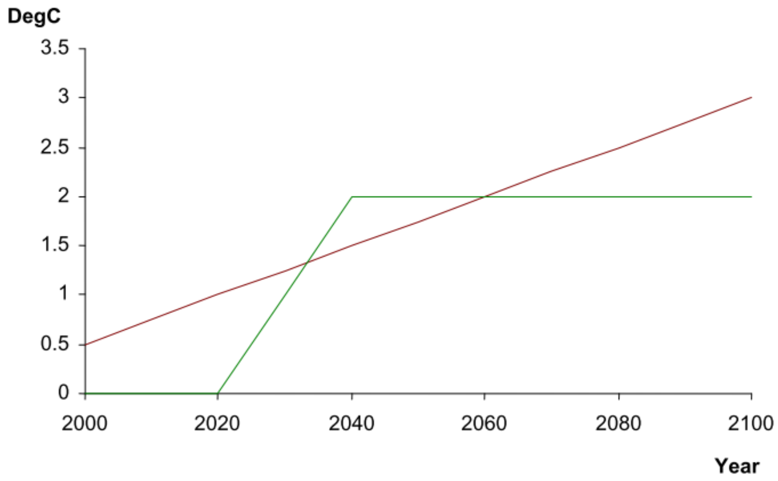
12.3.4 Damage function

PAGE has three impact sectors: economic, non-economic and sea-level rise. Impacts occur if the temperature increase (or its rate) is larger than a tolerable level (or a tolerable rate). Costly adaptation can increase tolerable levels (or rates). Neglecting the rate component for illustrative purposes, damages are proportional to $(\Delta T - \Delta T_{tol})^n$, where ΔT is the temperature increase, ΔT_{tol} is the tolerable temperature increase and n is an exponent (best guess: 2, range: 1.5–3). Figure 40 illustrates this approach. The red line depicts ΔT, which increases with time. The green line is ΔT_{tol}, whose shape can be chosen to minimize costs.[136] Only if the red line is above the green line, damages arise.[137]

[136] There are three input parameters for each impact sector and region to specify the shape of the tolerable temperature curve. The plateau, the start date of the adaptation policy, and the number of years it takes to have full effect.

[137] There are four input parameters for each impact sector and region that represented the reduction in impacts: the eventual percentage reduction, the start date, the number of years it takes to have full effect and the maximum sea level or temperature rise for which adaptation can be bought (beyond this, impact adaptation is ineffective).

Figure 40: Illustration of PAGE's impact function



Temperature and tolerable temperature by date
Source: Hope, 2011, Figure 3.

Damages are calibrated to the EU using a certain calibration temperature rise (best guess: 3°C) such that damages are a certain fraction of GDP (best guesses: economic damages: 0.5% of GDP; non-economic damages: 0.53% of GDP). For sea-level rise, the procedure is similar and for the calibration (best guess: sea-level rise of 0.5 meter), the best guess damages are a 1% reduction of GDP. The exponent of the impact function is lower for sea-level rise (best guess: 0.73, range: 0.5–1).[138]

PAGE considers potentially catastrophic impacts as so-called "discontinuities". It is assumed that the probability of a discontinuity increases with a temperature above a certain threshold (best guess: 0% at 3°C, 20% at 4°C, 40% at 5°C, and so on). This threshold cannot be affected by adaptation. If a discontinuity occurs, GPD drops by 15% (best guess). This does not occur immediately, but instead develops with a characteristic lifetime after the discontinuity is triggered (best guess: half-life of 90 years). Damages and adaptation costs in other regions are expressed as fixed fraction of the damages in the EU and summed by using the equity weighting scheme proposed by Anthoff et al (2009). The mitigation and adaptation costs can be fully equity weighted in the same way as impacts are.

12.4 Comparison

In this subsection we provide a comparison of the three damage models.

12.4.1 Overview of modelling approaches

The following table compares several modelling approaches of the damage models.

[138] For very high temperatures PAGE may show damages of more than 100% GDP. To prevent such an unrealistic result, it is assumed that damages start to "saturate" (best guess start at damages of 33% of GDP).

Table 16: Comparison of FUND, DICE and PAGE

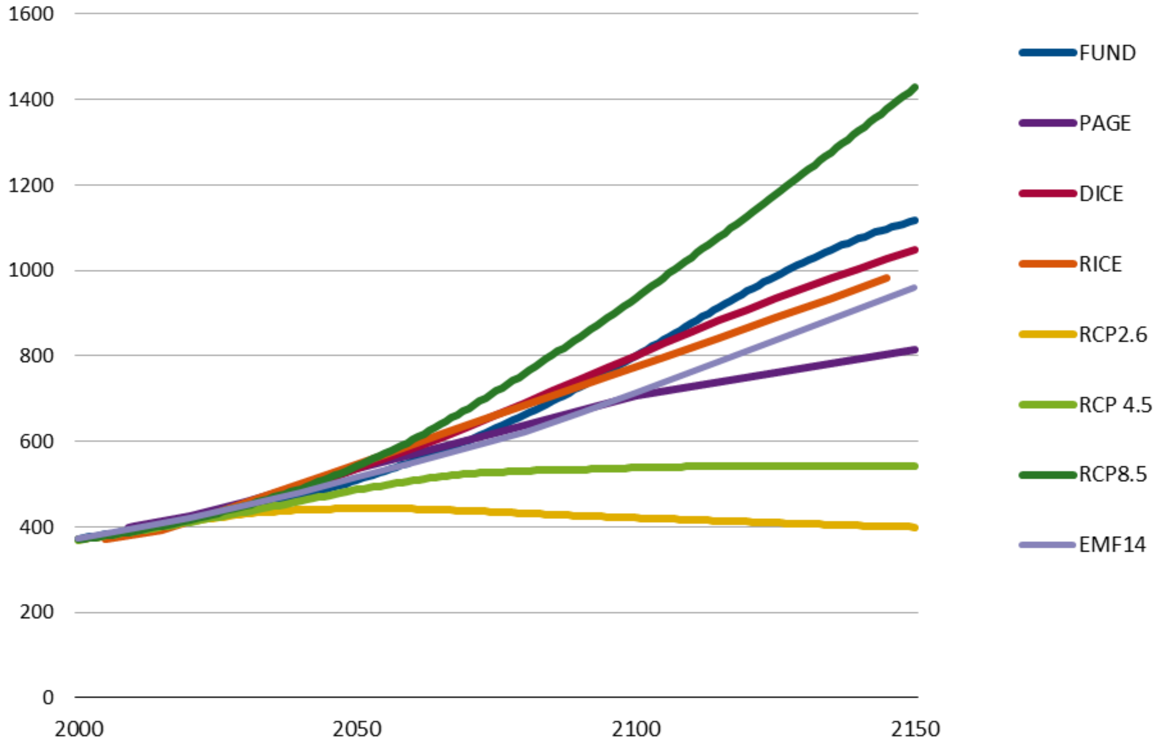
Damage Models Modelling approach	FUND Version 3.9	DICE Version 2013R	PAGE Version 2009
Regions	16	1	8
Model Type	Exogenous Growth	Optimal growth model	Exogenous Growth
Carbon Cycle	5-box	3-box	1-box
Non-CO2	CH4, N2O, SF6, SO2	Exogenous aggregate forcing	CH4, N2O, SF6, SO2; HFCs, PFCs
Impact sectors	14	1	3
Damage function	Sector-specific	Quadratic	Power function with uncertain exponent
Catastrophic climate change considered	In probabilistic mode via extreme tails of pdf	Implicit (25% increase of damages)	Yes (Prob. of steep rise of impacts above threshold)
Adaptation	Explicit for SLR, partly implicit otherwise	Implicit (damages net of benefits)	Explicit for all impact sectors
Equity weighting	Yes	No	Yes
Stochastic	Probabilistic mode possible	No	Yes
In Cost-Benefit Mode			
Mitigation efforts are implemented	Indirectly with policies that increase efficiencies in the economy	Directly with the costly emission control rate.	Emission level
Endogenous technological change	Learning-by-doing (only for abatement induced by policies)	No	Yes
Backstop technology	No	Yes	No

Source: own illustration, Infras

12.4.2 CO2 concentration, temperature, and GDP

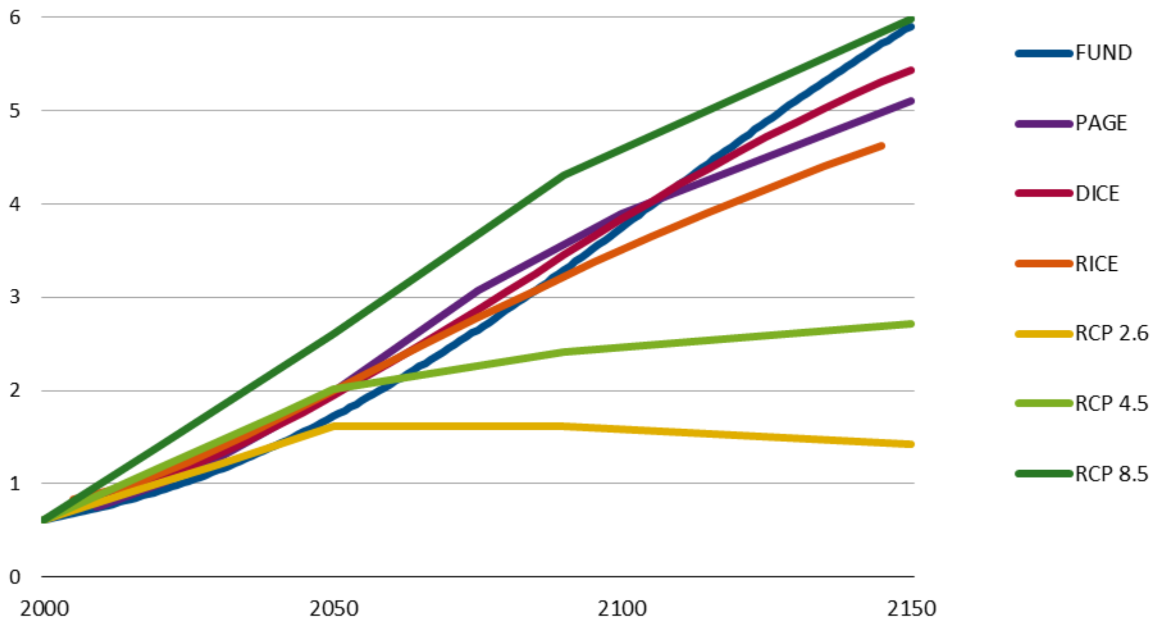
The following figure shows the atmospheric CO_2 concentration and temperature increases as given in the Mimi-Versions until 2300 and other scenarios. The trajectories of the models are similar and correspond to the RCP8.5-scenario at least in terms of temperature. They are far off the 2°C — let alone the 1.5°C target — given by the Paris Agreement.

Figure 41: Atmospheric CO_2 concentrations in ppm — Damage models, RCP and EMF14 scenarios



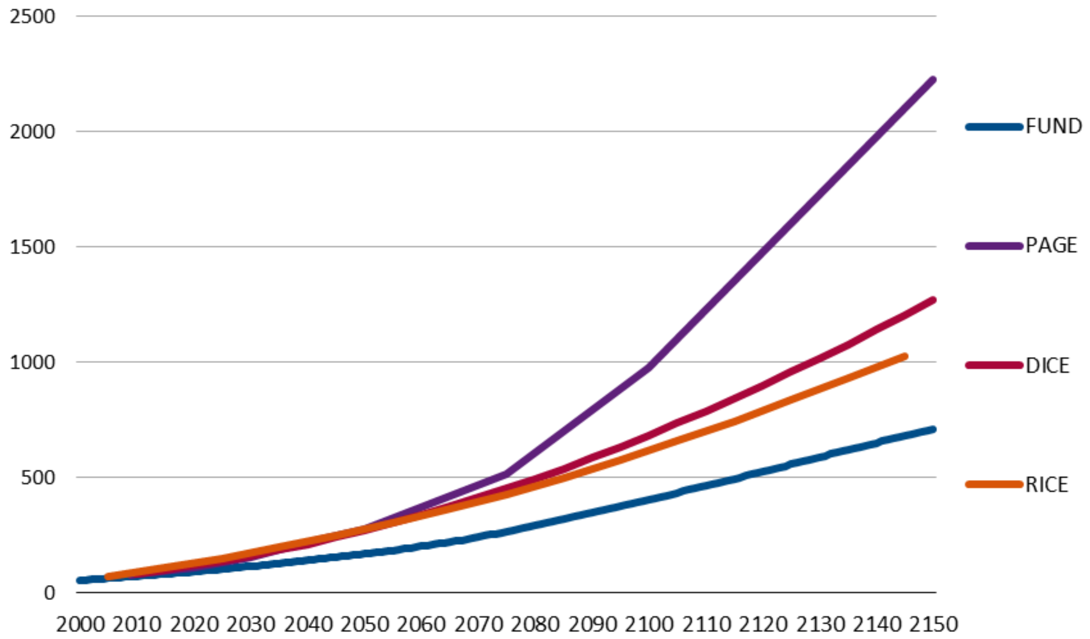
Source: own illustration, Infras. For damage models based on FUND's Mimi-Versions (see https://www.mimiframework.org/),for RCP-scenarios on https://www.iiasa.ac.at/web-apps/tnt/RcpDb/dsd?Action=htmlpage&page=compare and for EMF-scenario https://web.stanford.edu/group/emf-research/docs/emf14/WP1401.pdf (20.12.2019)

Figure 42: Temperature increase relative to pre-industrial in °C — Damage models and RCP scenarios



Source: own illustration, Infras. For damage models based on Mimi-Versions. See https://www.mimiframework.org (20.12.2019) and for RCP-scenarios IPCC AR5, WGI, chapter 12, Table 12.2. (Collins et al., 2013, p. 1055)
Side-note: RCP8.5 has a low temperature increase considering its high CO_2-concentrations. However, its 5 to 95% confidence interval for 2300 is 3.0 – 12.6 °C.

Figure 43: Global GDP per year in Trillion US-$$_{2019}$ (exclusive of abatement and damages) for damage models



Source: own illustration, Infras based on FUND's Mimi-Versions. See https://www.mimiframework.org/ (20.12.2019)

12.4.3 Damage function

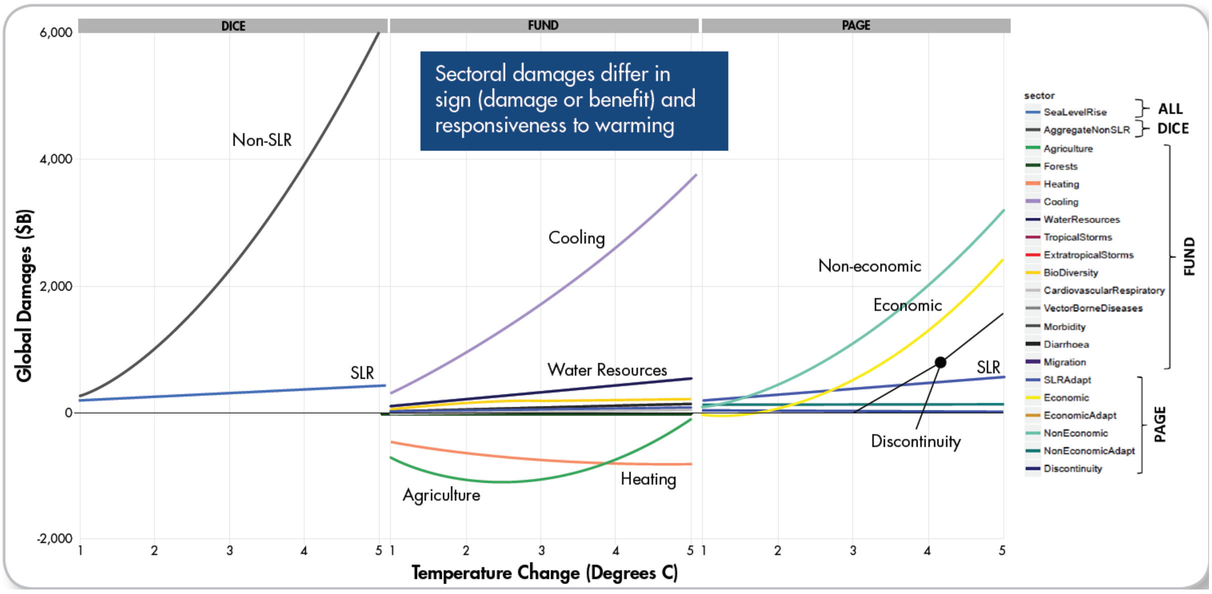
The following figures from Rose et al., 2014 illustrate the differences between FUND, DICE and PAGE regarding the damage function.[139] This concerns several dimensions:

- The models use different damage sectors.[140]
- Overall damages differ substantially. FUND exhibits lower global damages than DICE and PAGE for all levels of temperature change and FUND's net impacts are beneficial up to about 2.5°C, mainly due to the sectors heating and agriculture. The impacts on agriculture stay beneficial up until 5°C.
- Only PAGE explicitly models the impact of catastrophic events (starting at 3°C; called "discontinuity").
- DICE does not differentiate between regions (this has been tackled in its derivative RICE). In FUND, the damages in China play a crucial role, where impact are beneficial below 3°C due to agriculture but rise steeply due to the increasing cooling demand. In PAGE the regional differences are less pronounced.

[139] Note that the exact numbers depend on the scenario. Rose et al., 2014 used USG2 (for a description see the reference)

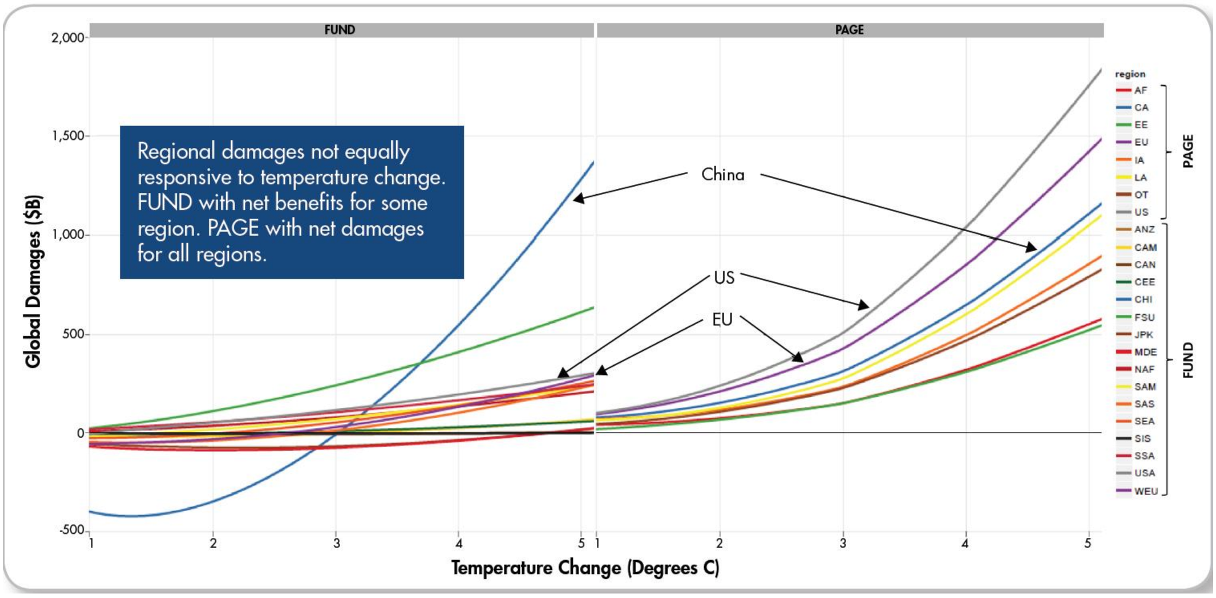
[140] Note that DICE2013R, as described in Section 12.1.4, does not explicitly model sea level rise anymore but aggregates sea level rise and other damages into one sector.

Figure 44: Model's global damages differentiated by sectors



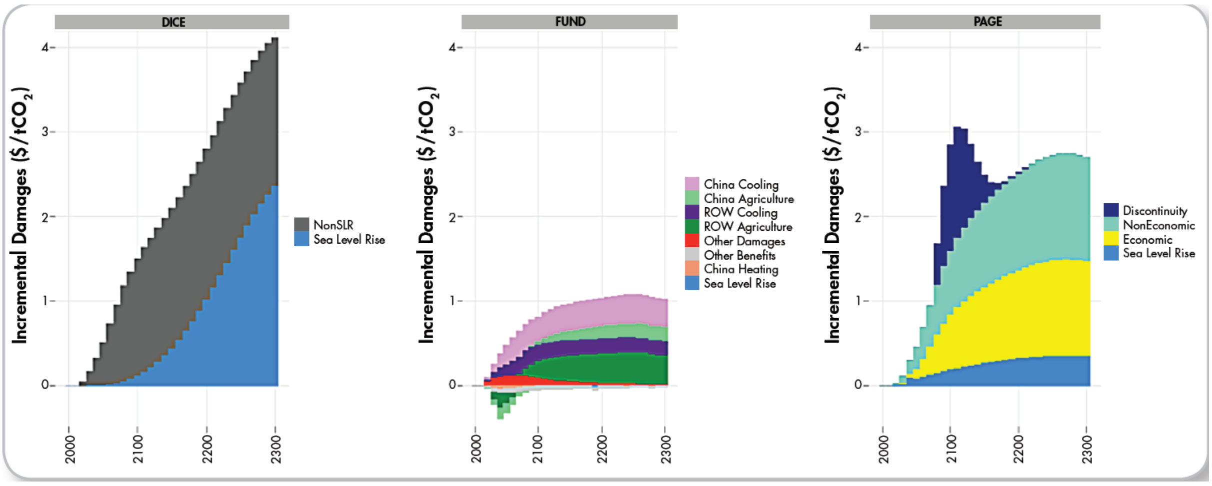
Source: Rose et al., 2014, Figure ES-8

Figure 45: Model's global damages differentiated by regions



Source: Rose 2014, Figure ES-9

Figure 46: Model's annual increments of global damages differentiated by selected sectors



Legend: Annual incremental damages are the additional damages (in $/tCO_2$) in a given year caused by a 1 GtC increase in 2020 (for the USG2-scenario).

Source: Rose et al., 2014, Figure ES-10

13 Quantitative impact assessment

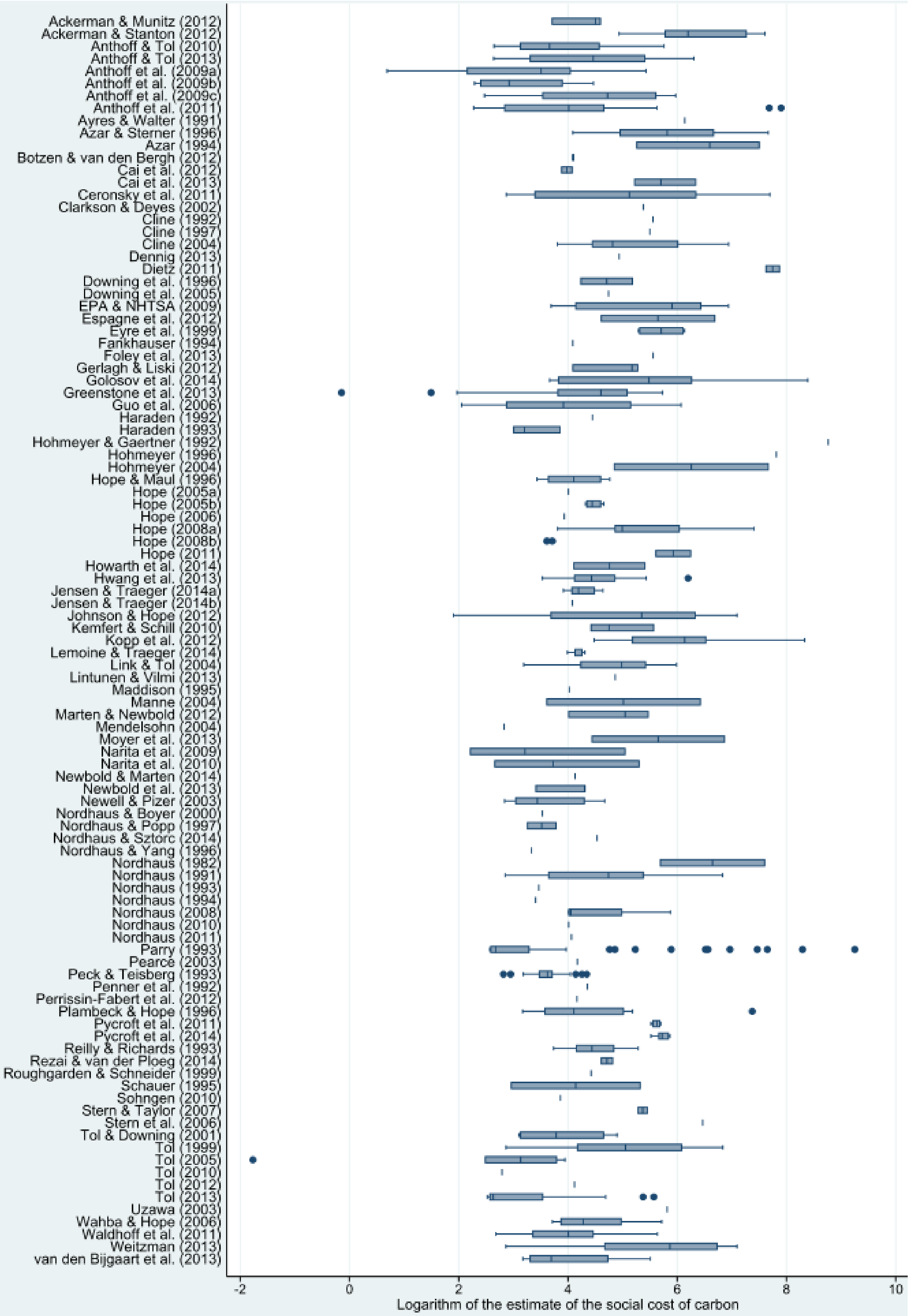
In the following we show the impact of the most important influencing factors on the SCC. In Section 13.1, we briefly discuss the range of absolute values of the SCC as determined by meta-analyses in the literature.

Subsequently, we focus on the relative changes if a single influencing factor is changed as part of a sensitivity analysis. Note that the relative changes are influenced by the set-up of the damage models, such that the changes must be interpreted as indicative. In Section 13.2.1, we present results using the Mimi platform, which allows us to define a common reference case. Finally, in Section 13.2.2, we show results from the literature.

13.1 Literature on SCC values

A meta-analysis on the climate change impacts revealed two main strands of literature. One strand specifically focuses on the damage function and compares the climate damages for a given temperature increase. The other strand compares the SCC, for which the damage function is only one among many parameters. In the following we show results of the second strand. Figure 47 shows that the SCC-range is large even for single studies (note the logarithmic scale) and is larger still when considering a large number of studies.

Figure 47: Estimates of the SCC per tC (*not* per tCO_2) in the literature normalized to emission year 2015 in 2010 dollars (logarithmic scale)



Source: Havranek et al., 2015

Table 17 provides a chronologically ordered overview of SCC values for selected meta-analyses (whereas the overview in Figure 47 shows single studies).

Table 17: SCC-Value from Literature in US$ per tCO_2

SCC (per tCO_2)		Base year[141]	Comment	Reference
Range: 1–34		1990	Meta-Analysis	IPCC SAR (1996)
av=29; range:14–57 from Clarkson and Deyes 2002 range:1–2 with DR=3% from Pearce 2003 av=25; md=4 (95%-PCT: 95) from Tol 2005		2000	other estimates: 0–400 $/tCO2[142]	IPCC AR4, WGII, Chapter 20 (Yohe et al., 2007)
Best guess=85		2000	For a BAU trajectory using PAGE	Stern, 2007
av=160 (sd=178) for PRTP=0% av=57 (sd=77) for PRTP=1% av=10 (sd=10) for PRTP=3% av=117 (sd=181) for all studies		Unclear	Statistical analysis using Tol-paper's method and more than 50 studies	IPCC AR5, WGII, Section 10 (Arent et al., 2014)
av=79 (sd=173)		Monetary: 2010 Time of emissions: 2015	Statistical analysis with 809 datapoints	Havranek et al., 2015
md=12 (DR=4.5% to 2050)	2–18 (model spread) 5–27 (5%–95% PCT)	Monetary: 2005 Time of emissions: 2020	Harmonized baseline trajectories using DICE, FUND and WITCH	Gillingham et al., 2016
av=185 (sd=182; md= 60) for PRTP=0% av=98 (sd=128; md=25) for PRTP=1% av=12 (sd=10; md=8) for PRTP=3%		Monetary: 2010 Time of emissions: 2015	as Tol, 2013 or Tol, 2005 (added data)	Tol, 2018

In the original sources, some values are given in $ per ton of carbon. A SCC of 100 $ per ton of carbon corresponds to 27.3 $ per ton of CO_2, as a CO_2 molecule weighs a factor of 44/12 more than C.
DR = discount rate; av = average; md = median; sd = standard deviation; PRTP = pure rate of time preference; PCT=Percentile
Source: See table; column "references".

IPCC's fourth assessment report (AR4) reviewed the then current literature up to 2007 and explicitly listed three studies, whose results are diverse but all below $50\$_{2000}/tCO_2$. This can probably be explained with the fact that the studies assume high discount rates. Almost at the same time the influential Stern Review was published (Stern, 2007), whose SCC value is not derived from a meta-analysis, but nevertheless included in the table. It is substantially higher ($85\$_{2000}/tCO_2$), chiefly due to its low discount rate and consideration of catastrophic events.

[141] Monetary basis and time of emission (unless otherwise stated)

[142] "Other estimates of the social cost of carbon span at least three orders of magnitude, from less than US$1 per tonne of carbon to over US$1,500 per tonne", in IPCC AR 4, WGII, Chapter 20 (Yohe et al., 2007, p. 813 Executive Summary)

IPCC's fifth assessment report (AR5; heavily based on Tol, 2013 [143]) and Tol, 2018 fit the SCC values of various studies to a probability density function and undertake a statistical analysis. SCC values are distinguished by the discount rate. Havranek et al., 2015 essentially do the same.

The results from the meta-analyses differ for several reasons:[144]

- Data selection issues (e.g. newer meta-analyses contain more studies, selection of existing studies, selection of data points within studies if no or several best-guess are presented, weighting schemes if studies present several results or if several studies are not independent due to similar underlying methods, authors and models)
- Statistical methods to summarize data (e.g. cut-off of outliers, normalization to single emission year and inflation adjustment to a base year)

Statistical meta-analyses have been developed and advocated by Richard Tol on several occasions. Yet, it is questionably how meaningful meta-analyses of SCC values are in the first place. Apart from the differentiation between different PRTP, it is unknown how the various influencing factors (especially normative factors) are handled in the underlying studies (e.g. is there equity weighting, are catastrophic events accounted for, which damage models is used, etc.[145]). Howard & Sterner, 2017 criticize that it is common practice in the literature to cite earlier estimates or to update previous estimates, which results in a multiple or duplicate publication bias. They also note that older — possibly multiply cited — studies tend to exhibit lower SCC estimates as they usually do not account for e.g. non-market and catastrophic climate impacts in addition to market impacts.

Nevertheless, Havranek et al., 2015 find that the year of publication is not systematically related to the magnitude of the reported SCC. They also highlight that studies published in better journals tend to report larger estimates. Finally, they find that studies that report uncertainty associated with their central estimates tend to report larger SCCs (112 instead of 79$\$_{2000}/tCO_2$).[146]

Considering all these arguments, we think that the results presented in Table 17 are *no meaningful guide to assess the SCC*.

13.2 Sensitivity analysis on the impact of influencing factors

13.2.1 This study's calculations using the Mimi framework

The Mimi platform allowed us to analyse results for the following model versions: FUND3.9 with and without equity weighting, RICE2010, DICE2013R and PAGE09. (see Table 18).

[143] Tol has been one of the Coordinating Lead Authors and has updated his Tol, 2013 results with new studies to produce the AR5 figures.

[144] See also Howard & Sterner 2017 for a more in-depth discuss on the possible biases of meta-analyses in the context of damage function estimates.

[145] Havranek et al., 2015 statistically analyze some influencing factors in a dataset of 809 SCC values, but do not get significant results, probably because the multitude of influencing factors defy any statistical analysis.

[146] "Only 267 out of the 809 estimates in our data set are reported together with a measure of uncertainty. These estimates are on average much larger than the rest of the data: the mean estimate with uncertainty is [112] (in contrast to [79] when all the estimates are considered) and the median is [66] (in contrast to [27]). In other words, authors who provide a probabilistic distribution of estimates tend to report much larger median values of the SCC than authors who only report their best-guess estimates." (Havranek et al. 2015, p.12). We adjusted the original values, as the study displays social costs per ton of carbon.

Table 18: Sensitivity Analysis for SCC estimates in $\$_{2019}/tCO_2$

	Value Sensitivity Analysis	FUND (without EW)	FUND-EW (with EW w.r.t WEU[147])	RICE	DICE2013	PAGE09
Reference Case	-	**4.6**	**211.5**	**28.2**	**34.9**	**80.9**
Pure rate of time preference RC: δ = 1%	0%	17.3	719.3	193.7	95.6	119.6
	2%	1.2	52.8	12.9	17.7	58.1
Fixed Discount rate RC=Ramsey Discounting	0.1%	1233.8	n/a	14671.2	2468.4	1519.4
	1%	105.0	n/a	613.2	477.3	412.0
	3%	9.9	n/a	39.3	57.5	39.9
Elasticity of marginal utility of consumption RC: η = 1.5	0	105.0	105.0	613.2	477.3	412.0
	0.5	32.4	105.4	183.6	176.9	157.1
	1	11.8	136.8	72.8	81.9	n/a
	2	1.7	338.0	14.3	18.5	46.6
	3	-0.2	-2339.1	5.2	6.8	80.9
Climate Sensitivity RC: CS = 3	1.5	-0.2	43.5	11.2	11.9	n/a
	4.5	7.3	292.6	50.1	71.4	214*
Growth rate of per capita consumption RC: g as given by model	+ 50% in each region	6.4	348.6	n/a	n/a	24.9
	- 50% in each region	4.7	127.2	n/a	n/a	504.7
Emission Year RC: 2015 (current SCC**)	2030	8.1	320.0	n/a	57.7	39.1***
	2050	13.8	442.0	n/a	101.3	12.6***
	2075	23.5	551.1	152.6	176.9	7.0***
	2100	37.2	625.2	n/a	272.9	1.1***
Emissions scenarios§ RC: given by model (see Figure 41)	RCP2.6	3.1	108.4	n/a	28.9	n/a
	RCP4.5	4.1	173.9	n/a	31.2	n/a
	RCP8.5	4.9	234.4	n/a	36.2	n/a

EW= equity weighting; RC = reference case.
* PAGE uses as input the transient climate response, which we doubled (from 1.7 to 2.8).
** SCC at time the emission takes place

147 We normalize the equity weighted version of FUND with respect to the FUND-region WEU (western Europe).

*** Due to an error in the original Mimi-code, PAGE SCC-values are not in current but in present values (i.e. after discounting to the present). SCC thus decrease for later emission years.
§ For technical reasons only emissions can be manipulated in the Mimi-Versions. We thus changed the original emissions to roughly approximate the RCP's CO_2-concentrations as given in Figure 41. As this involves considerable effort, we only applied these manipulations to FUND and DICE.
Source: Calculation using https://www.mimiframework.org/

Some runs could not be performed for specific models, indicated by n/a. The table depicts the results for the reference case[148] in the first line as well as the results for ceteris paribus deviations with respect to selected influencing factors.

To test FUND's sensitivity, we also changed certain parameters of important impact sectors. Note that these changes are ad-hoc and not based on any underlying literature. We do not claim that these new parameters are more plausible than the original ones. This is merely a test of sensitivity. The reference value of FUND, SCC=4.63, changes as follows, if these parameters are changed:

- Expenditure on space cooling (see Section 12.2.5.1): Reduce ε from 0.8 to 0.4 → SCC'=1.59.
- Expenditure on space cooling (see Section 12.2.5.1): Reduce β from 1.5 to 0.75 → SCC'=–0.16.
- CO_2 fertilization component of agriculture $A_{t,r}^{CO_2-fertilization} = \gamma_r ln \frac{ppm_t(CO_2)}{275}$ (see Section 12.2.5.2): Reduce γ_r by 50% for all regions→ SCC' = 8.1.
- Carbon Cycle Feedback Biosphere: Increase proportionality constant by a factor of 2 → SCC'= 5.16.
- Ecosystem Sector: Increase proportionality constant by a factor of 2 → SCC'= 5.30; Increase by factor 4→ SCC'= 6.61.

From the sensitivity analysis we derive the following insights:

- SCC estimates for the reference case differ between models. FUND (without equity weighting) exhibits the lowest value, followed by RICE/DICE and PAGE.[149] FUND-EW (FUND with equity weighting with respect to Western Europe) has the highest SCC-estimate.
- FUND-EW has much higher SCC value than FUND. In the reference case it is 7.5 times higher. This factor is especially sensitive to inequality aversion η and the pure rate of time preference δ (the factor increases if η increases and δ decreases). This highlights the huge influence of equity weighting on overall modelling results.
- FUND's equity weighted results are highly depended on the benchmark per capita income used for the normalization. We used Western Europe as our benchmark, as this is where Germany is located geographically. Yet, Germany has a higher per capita GDP than Europe and lower than the US. Normalizing for the region USA, the SCC in the reference case increases to 284.9$\$_{2019}/tCO_2$.

[148] In the reference case, all models use the following parameters: δ=1%; η =1.5; Ramsey Discounting scheme; CS = 3; emission year 2015. The growth rate per capita g and the emission scenario are not harmonized in the reference case but as given by the underlying scenarios of the models.

[149] Note that DICE has no equity weighting, as it only features one region. In the regional version of DICE called RICE, equity weighting is not considered. PAGE does consider equity weighting (see Section 12.3.4).

- The influence of the pure rate of time preference δ is, as expected, substantial and non-linear (especially a PRTP of zero highly increases the SCC).
- Instead of using a Ramsey Discount rate (i.e. time-varying due to the growth discounting part) a fixed discount rate can be applied.[150] Using a fixed discount rate of 0.1%, the SCC is very high for all models. Even for a fixed discount rate of 3 percent, the SCC are still higher than in the reference case where the pure rate of time preference is 1 percent. This shows the huge impact of the growth discounting component (given the huge increase in global GDP that underlie all models; see Figure 43).
- A higher elasticity of marginal utility of consumption η decreases the SCC due to the impact on growth discounting. In addition, FUND-EQ and PAGE exhibit impacts on the equity weighting scheme such that, especially for high values of η, diverging values result.
- The influence of the climate sensitivity is, as expected, substantial and almost linear.
- Changes in the growth rate of per capita consumption have two impacts: (i) increase the growth discounting component (which decreases the SCC) and (ii) increase GDP (which increases damages). Depending on the specification of the model and the reference case, the impacts of this sensitivity analysis thus differ substantially among models. For DICE/RICE, such an analysis was not possible as they are optimal growth models where growth rates are endogenous variables and hence difficult to adjust.
- A later emission year increases the SCC, essentially because marginal damages are higher in later periods and the absolute level of climate change is higher as well (see Section 8.2). Note that the SCC are given in current values, that is, they represent the year of emissions before discount to the present. For PAGE however, results are in present values (i.e. after discounting to the present) due to an error in the code of the Mimi framework. The SCC thus decrease with emission time for PAGE (highlighting once again the importance of discounting).
- Emission scenarios have a significant influence, as lower emissions results in lower SCC. FUND-EW exhibits the highest relative influence. A reason may be that damages in poorer countries show the highest relative damage-response to a change in the emission scenarios. This is more relevant for the SCC in the equity weighted version.
- FUND's results are sensitive to the respective parameter choices of single impact sectors such as agriculture or cooling.

[150] We tested the setting η=0 such that δ plays the role of the fixed discount rate. For η=0 the equity weighing scheme in FUND-EW cannot be used any more.

There are a few notes to keep in mind regarding these results:

- The sensitivity analysis is conducted in the damage models framework, where emission scenarios remain fixed. In a CB-IAM framework, the results would differ. If, for example, the pure rate of time preference is decreased, the optimal emission level would be adjusted downwards, subsequently impacting the calculated SCC values. Since such optimizations are complex, we could not model the impact of optimization. However, given that the impact of emission scenarios is significant, we assume that SCC would change considerably if the sensitivity analysis were conducted in a CB-IAM framework.
- The models have different internal base-case years. To guarantee consistency, we inflated all monetary values to the year 2019.[151] Specifically FUND uses $US\$_{1995}$ such that we use an inflation factor of 1.7, while PAGE uses $US\$_{2008}$ leading to an adjustment with a factor of 1.21 and DICE/RICE a factor of 1.34 (based on $US\$_{2005}$).
- PAGE is a stochastic model (and FUND could be run stochastically as well). Yet all SCC-estimates from Mimi stem from single model runs using the best guess estimates.
- Finally, in this sensitivity analysis we only looked at a damage model setting and did not change any parameters related to the *mitigation module*. This is for two reasons: First; to calculate the subsequent changes in the SCC, we would have to run an optimization, which is not easily doable in the Mimi framework. Second, as mentioned, CB-IAM are not the focus of this study and emissions scenarios are thus considered exogenous.

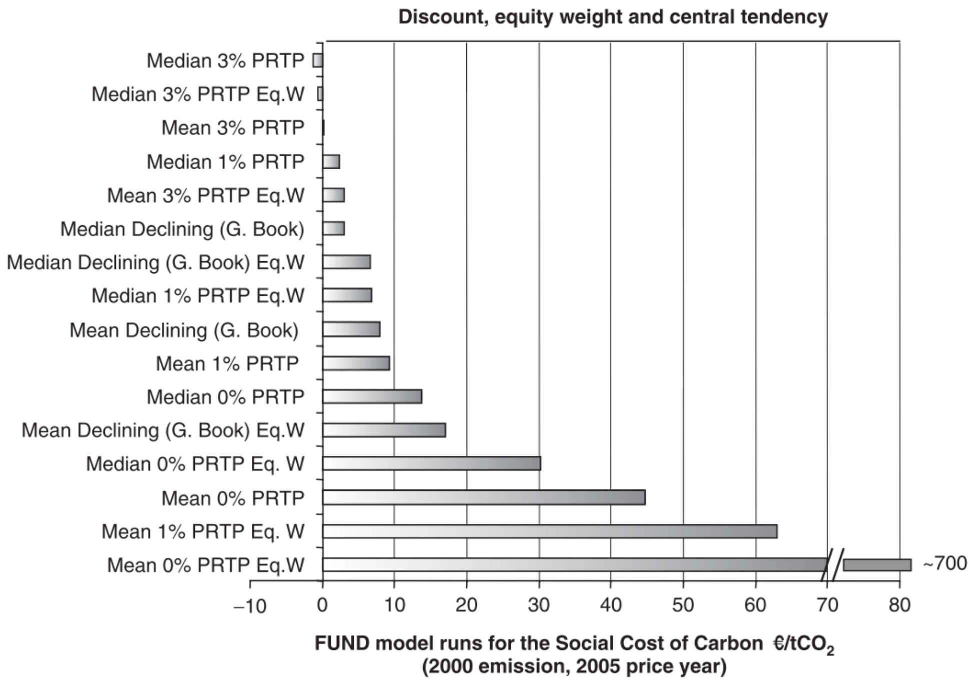
13.2.2 Literature overview

Using the Mimi-Platform, we could analyse only certain influencing factors (those that can be manipulated without considerable effort). In this chapter we thus provide an additional overview on the literature's quantitative impact estimates of this as well as other influencing factors.

Figure 48 shows results of a sensitivity analysis conducted by Watkiss, 2011, using a stochastic version of FUND. It roughly confirms our results and illustrates which factors dominate the SCC. As additional influencing factor, it compares the median and average (=mean) of the results, since changing the measure by which the result is presented is important in communicating the finding. The mean SCC is generally larger than the median, since ist distribution is not symmetrically but positively skewed.

[151] Using the CPI Inflation Calculator at https://data.bls.gov/cgi-bin/cpicalc.pl (07.01.2020).

Figure 48: Sensitivity Analysis of SCC estimates using a stochastic version of FUND in €$_{2005}$/CO_2



Legend: "Declining (G. Book)" refers to a declining discount rate according to the UK Green Book (see Table 10)

Source: Watkiss, 2011, Figure 2.

Table 19 provides a literature overview on the differences of results due to certain influencing factors (with a focus on those factors we could not analyse in Section 13.2.1). Given the large and multifaceted literature on this topic, we do not claim completeness (see also e.g. the excellent review by van den Bergh & Botzen, 2015 or Table 3 in van den Bergh and Botzen, 2014).

Note that we chose to display only relative impacts and that these numbers depend on the context. For example, for the inclusion of catastrophic climate events it makes a big difference which discount rate is used. For higher discount rate, the effect on SCC is small, as even very large future climate damages receive a very small weight for the present SCC value.

Table 19: Impact of influencing factors in the literature

Influencing factor	Increase of SCC by factor*	Comment	References
Damage model choice	4	Difference between FUND, DICE and PAGE	IAWG, 2010
Socioeconomic and emission scenarios	1.5	The scenarios of this study are outdated. Most feature high emissions	IAWG, 2010 (Tables 2 and 3) or IAWG, 2016 (Table A2-A4)
Uncertainty w.r.t long-run economic growth (DICE)	1.5	Focus on theoretical derivation; Numerical assessment only add-on	Jensen & Traeger, 2014 (Figure 4)
Uncertainty of climate sensitivity (PAGE)	1-29–1.85	Thin-tailed pdf of CS is replaced by a fat tail	Pycroft et al., 2011
Alternative damage functions including catastrophic risks** (DICE)	3	Using η=1.4, δ=0.14%	Kopp et al., 2012
Alternative damage functions including catastrophic risks (DICE)	4	Alternative damage function sharply increases above 3°C	Ackerman & Stanton, E2012; Figures 4 and 5
Alternative damage functions including catastrophic risks (DICE)	3-5	Alternative damage function based on a statistical meta-analysis of literature results (including catastrophic impacts for upper bound)	Howard & Sterner, 2017
Including catastrophic risks (PAGE)	4.2	As compared to the Stern review	Dietz, 2011
Including tipping points (FUND)	>3	Collapse of the Atlantic Ocean Meridional Overturning Circulation; large scale dissociation of oceanic methane hydrates; and climate sensitivities above "best guess" levels	Ceronsky et al., 2011
Scarcity of Non-Market Goods (DICE)	1.43 (year 2020) 1.58 (year 2100)	Relative values of non-market goods increase compared to market goods as the former get scarcer with time and substitutability is limited	Drupp & Hänsel, 2018
Aggregation method of expert views on δ and η (DICE)	2	A single run with the experts' mean of δ and η results in lower SCC than separate model-runs for each δ/η-combination and taking the mean of these runs.	Hänsel et al., 2020
Agricultural sector (FUND)	2	Updated damage function incorporating the most recent empirical estimates	Moore et al., 2017

Normalization region for equity weighting (FUND)	60 (for δ=0%) 30 (for δ=1%) 10 (for δ=3%)	For Scenario A1B. Our estimation roughly using the 5%–95% range of the data points.	Anthoff et al., 2009 (Table 2)
Growth vs. level effect on damages	Up to 100	See Figure 21	Newell et al., 2018

* If not explicitly stated in the study, we estimate the factor.

** also called in the literature: low-probability/high-impact climate events, fat-tailed risks, abrupt climate change or extreme & discontinuous outcomes.

Source: own illustration, Infras (inspired by van der Bergh & Botzen, 2015, Table 3)

14 Expert survey as alternative to derive SCC

Citing the uncertainties of damages cost models, Pindyck, 2019 provides an alternative approach to derive the SCC. He uses an expert survey where he does not simply ask participants directly what their best guess for the SCC is. Instead, he uses an indirect way, based on a simple "desk model". He assumes that SCC results are mainly driven by catastrophic events, as focusing on best-guess scenarios would entail only small SCC. He discards a low discount rate as a further reason of a high SCC, as a low discount rate conflicts with the opinion of a vast majority of survey-participants (the average discount rate of the participants is approx. 3%).

Pindyck, 2019 asked participants to state the probability that GDP in 2066 under a business as usual case drops by 2%, 5%, 10%, 20% and 50%. In addition, he asks them which emission reductions would be necessary to ensure with high confidence that no drop of 20% or greater occurs. Using these (and further input), Pindyck, 2019 calculates an "average SCC". He defines the average SCC as "the present value of the flow of benefits from a large reduction in emissions now and throughout the future, divided by the total amount of the reduction" (ibidem, p. 8). The benefits in this case are the prevented large-scale damages from catastrophic events (without considering smaller best-guess damages). He explicitly states that his approach would not be possible with the marginal definition (where in a strict sense only the impact of one additional ton of emitted CO_2 is evaluated).[152]

Pindyck, 2019 states that "this approach acknowledges that currently the best we can do — especially with regard to extreme outcomes — is rely on the opinions of experts" (ibidem, p. 3) and "different experts will arrive at their opinions in different ways. Some might base their opinions on one or more IAMs [climate damage models], others on their studies of climate change and its impact, and others might combine information from models with other insights" (p. 4).

Feeding the participants responses into the simple desk model, he arrives at mean values of the "average SCC" of 80 $/t$CO_2$ for a standard set of assumptions.[153] Using different assumption on discarding outliers, on responses from participants with self-stated low confidence and on distribution functions, the mean value could be lower and drop to a minimum of appr. 30 $/t$CO_2$.[154]

It is noteworthy that the climate scientists' answers yield a much higher average SCC than economists' answers (for a standard set of assumptions 86 $/t$CO_2$ as compared to 47 $/t$CO_2$).

Note that Pindyck, 2019's method is but one among many possible methods to consider expert opinions. For all those methods it is important to prevent introducing a sampling bias in the results and to communicate clearly the implications of a sampling bias for the result's interpretation.

[152] Average SCC have additional advantages in Pindyck's view: First, they are less sensitive to the choice of the discount rate, as not only the benefits but also the present value of the emission reductions (basically the accumulated reduction over a time horizon, which depends on the discount rate) decreases in the discount rate, such that the effects partly cancel each other out. Second, they depend less on the underlying emission scenario.

[153] See table 4: Group "All", column "SCC: Highest R^2".

In the original publication, the numbers are in $/tC

[154] See table 5: Column "All – High Confidence", line "Gamma"

15 Main findings for damage cost perspective

Damage models aim to monetarize climate impacts and thus have potential applications supporting climate policy. The metric commonly used is the *social costs of carbon* (SCC), which represents the damages caused by the emission of an additional ton of CO_2. Despite considerable research effort conducted over the last decades on the economics and natural science of climate change, damage models still face **several severe limitations** at various dimensions calculating the SCC. Some limitations have been gradually improved upon, but the general issues remained largely unchanged since the early stages of their development (see also e.g. the critical reviews by Ackerman et al., 2009, Stern, 2013, Van den Bergh & Botzen, 2015, Pindyck, 2017 or Heal, 2017. There exists thus no consensus on the order of magnitude — let alone the value — of the SCC in the literature.

In the following we list and categorize the major factors influencing the SCC (for an explanation of the categories see Section 19.2).

Parts of the uncertainty stem from the underlying **scenarios and normative choices**. Those influencing factors can be chosen by policymakers. Subsequently, modelers have little discretion regarding implementation:

- The SCC increase for a **high-emission scenario**. This is because high emission scenarios lead to a high underlying temperature increase and damages caused by the emission of an additional ton of CO_2 increase with the underlying temperature (convex damage function).
- The future GDP level is determined by the **socioeconomic scenario** (mainly related to economic and population growth). Most damage models assume a steady GDP-growth, which is not affected by climate change. Climate damages are subsequently calculated as a fraction of the baseline GDP level. This has two major implications. First, future generations are assumed to be much richer (even accounting for climate damages), such that especially in a utilitarian setting the present generation ought to invest only little in climate mitigation. Correspondingly, assuming a higher GDP growth rate decreases the SCC. Second, a higher GDP growth rate increases the future GDP level, which leads to higher absolute damages. This increases the SCC and (partly) offsets the first effect. As GDP-growth rates differ among regions, those effects differ as well.
- The treatment of intergenerational equity boils down to the choice of the **discounting scheme and related parameters**. If the wellbeing of future generations is valued higher, the discount rate is lower and the SCC increase. There are essentially three discounting schemes: using a fixed discount rate, using a predetermined declining discount rate, or using Ramsey discounting (which combines fixed time-discounting with variable growth discounting). If Ramsey discounting is applied, several input parameters play a role: the pure rate of time preference, the economic growth rate (see previous bullet point), and intergenerational inequality aversion.
- Related to discounting is also the choice of the **time horizon** for modelling. If the chosen discount rate is high, damages in the far future become irrelevant to the SCC estimate. With a low discount rate on the other hand, a longer time horizon would also reflect damages in the

far future and in particular slow-onset events such as Sea Level Rise. Choosing a longer time horizon thus only affects the SCC for a low discount rate.

- A related issue is the treatment of intragenerational equity (among people, nations or regions). Accounting for the equity within a generation essentially means that the valuation of damages in poorer countries is increased: In a utilitarian setting, a lower consumption level automatically implies a higher impact for a given damage (due to decreasing marginal utility of consumption). In addition, some models correct for the feature that low GDP levels entail low damages. Those effects are accounted for in the **equity weighting** scheme. The impact of equity weighting on the SCC also depends on the region the results are normalized upon. If normalization is with respect to a rich region, the SCC increases.[155]
- **Risk management choices** are relevant in a non-deterministic setting. Climate change may result in large damages, which have a major influence on cost estimates (especially if a high-risk aversion is assumed).

Another part of the uncertainty stems from **structural elements**. These influencing factors can be chosen by policymakers via the choice of the model(s) on which their decisions shall be based. Modelers hence have large discretion regarding implementation:

- The processes of the **climate system** translate emissions of greenhouse gases into geophysical impacts. Dedicated climate and earth system models comprise many components such as the carbon cycle, climate system responses (including extreme events), and sea-level rise. Those results can be used to calibrate in this respect much less complex damage models.[156] Yet, even dedicated, sophisticated models feature large uncertainties. The most prominent aspect is the average temperature increase for a given amount of GHG emissions (metric climate sensitivity and related concepts). The larger the temperature increase the higher the SCC. There are, however, other important aspects of climate change, which are usually not explicitly included in damage models. Examples are changes in precipitation patterns or changes in the intensity and/or frequency of extreme events (such as floods, droughts, storms, etc.).
- Damage models need **damage functions** to translate geophysical impacts into monetary values. Damage functions can be clustered into three types: they are either (1) aggregate and highly stylized, (2) sector-specific enumerations, or (3) based on macroeconometric estimates. To provide an undistorted picture, a damage function ought to include impacts of all sectors affected by climate change as well as take into account regional differences and indirect effects. This is a tall order for all three damages function types. Especially for high temperature increases and long-term effects there exists little data on which one can base assumptions about future developments. Specification and calibration of damage functions thus remain in large parts ad-hoc. There is also the essentially unresolved debate whether

[155] Note that some damage models (most notably RICE, the regional version of DICE), use so-called "Negishi-weights" to counterbalance the equity weighting implied by the decreasing marginal utility of consumption. Such models thus explicitly do not use equity weighting, arguing that this would imply huge intraregional wealth transfers, which are not observed in the real world. Correspondingly, the SCC is lower in such models (at least if normalized to rich countries).

[156] Given the constrained computing power and broader scope of damage models, there is none that incorporates a full-scale climate model.

climate change affects only the GDP-level or in addition the growth rate of GDP. The latter case leads to much higher damages in the long run as the growth effects accumulate.

- Damages can be decreased through **adaptation** efforts (*net* climate damages are the damages considering lowered impacts due to adaption plus the costs of adaptation). If damage models consider adaptation possibilities and related costs they do so either (1) implicitly and without costs as part of the socio-economic scenarios (which assume a certain resilience of societies and economies), (2) explicitly and entailing costs on a *aggregate* level, or (3) explicitly and entailing costs for *specific* sectors. The three approaches may also be used in parallel. The adaptability of future generations to a changing climate is essentially unknowable as it depends on various aspects (e.g. future technologies, governance, or resilience of societies) and large regional differences exist.
- If **technological change** is also modelled with respect to the costs of adaptation it has an impact on adaptation and thus net damage estimates.
- Only relevant for cost-benefit models (which consider damage and mitigation in parallel) is the difficulty to predict the scale and influence of future **abatement technologies and technological change.** This has a major influence on the mitigation costs and correspondingly on the endogenously determined emissions in cost-benefit models. This in turn influences the damages.

Finally, there are **exclusion choices**. The SCC can in principle be calculated without considering those influencing factors. Yet, we strongly recommend to only consider damage models for supporting climate policy that take them into account. Inclusion should thus be the default case and exclusion an explicit choice. Subsequently, modelers still have substantial discretion regarding the specific implementation.

- Damage models need to define an **approach to deal with uncertainties** of all the previously listed influencing factors. Uncertainty is present because of (1) the long time-horizon of the analysis, (2) understanding of crucial parts of the earth system (e.g. feedbacks or tipping points) is limited and (3) the economics to monetarize and aggregate impacts are contested. Early damage models have been run deterministically using ad-hoc assumptions and best-guess values of the uncertain parameters, largely neglecting uncertainties. It has become best practice, however, to run models stochastically. This allows to at least partly account for parametric and structural uncertainty (see Section 2.3.1). Unfortunately, the quantification of uncertainties remains incomplete and contested.
- Non-linearities and feedbacks in the climate system may cause climate change to trigger so-called “tipping points”, which would cause parts of the earth and climate system to permanently switch to a new, large-scale state (e.g. collapse of polar ice sheets, breakdown of the oceanic thermohaline circulation, dieback of tropical forests, permanent changes of the monsoon circulation). Those low probability, high impact events may entail tremendous damages and are thus often referred to as **catastrophic climate change**.[157] The related

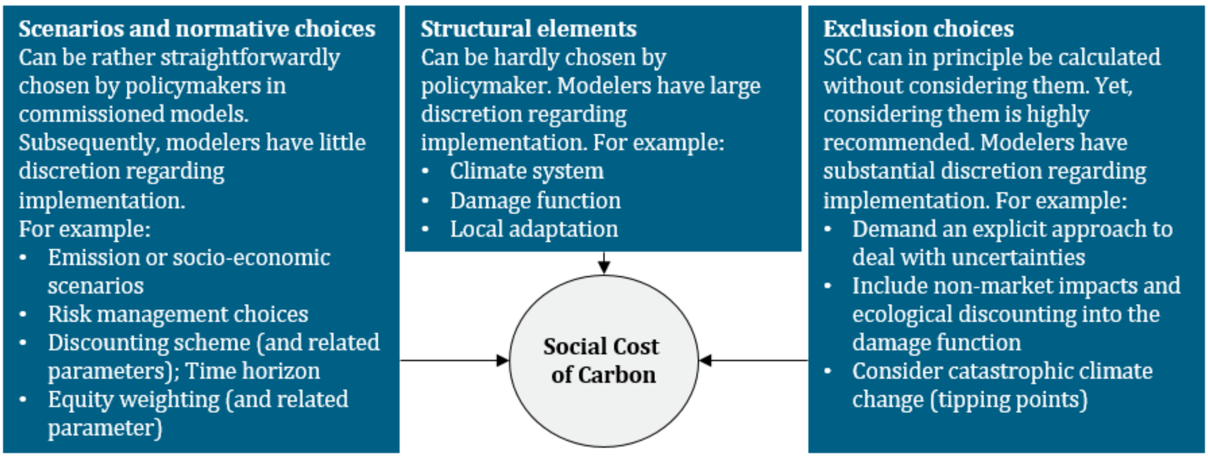
[157] Note the difference between extreme events and catastrophic events. Extreme events are events that already occur under the current climate (such as droughts or storms), but which may become more severe or more frequent under a changing climate.

uncertainties are inherently difficult to account for, and especially so in the present setting as they must be monetized. Damage functions thus treat catastrophic damages either not at all, incompletely or arbitrarily. Sometimes they are considered using an ad-hoc surcharge. Parts of the literature claim that the potential for catastrophe should be *the* essential driver for climate change policy in the spirit of an insurance approach. They thus call for limiting climate change to a certain threshold that shall not be crossed if the possibility of catastrophic damage is to be minimized.

- Climate change entails a variety of **non-market impacts**, which are either not directly connected to human wellbeing (e.g. biodiversity loss) or for which no direct market valuation exists (i.e. increased mortality). To provide a complete picture, it is important to account for those impacts. This is difficult, however, because non-market effects must be monetized and translated into the economic metrics of the damage models (e.g. GDP or total consumption). The corresponding methods are controversial and subject to great uncertainty (using e.g. the willingness to pay to prevent certain impacts or the statistical value of life).
- Finally, models ought to consider the limited substitutability between natural and market goods (e.g. using **ecological discounting**). There are various ways to extend the damage function accordingly, but data is scarce, and methods differ considerably.

Figure 49 provides an overview over those influencing factors and their categorization.

Figure 49: Social costs of Carbon: Overview and categorization of influencing factors



Source: own illustration, Infras

Damage models — boiled down to the basics — model that emissions of greenhouse gases cause climate change, monetize the resulting biophysical impacts and aggregate those values across space and time. Each of those steps is connected with uncertainty and there are many degrees of freedom regarding the modelling approach. Consequently, developers of damage models have a considerable discretion to determine the SCC. By prescribing requirements for scenarios and

Catastrophic events, on the other hand, are large-scale and long-term fundamental changes of the climate system. There are impacts where this categorisation is not clear cut, such as changes of the monsoon circulation.

(normative) choices as well as demanding obligatory extensions of the damage function, this discretion can be partly constrained by users.

An alternative way to derive SCC are expert elicitations (these studies either ask for SCC directly or deduce them from related answers). The results are as uncertain as those of models, since experts have little means to provide more robust answers than models. Moreover, many expert opinions will again be based on models.

While all models that aim to model complex real-world aspects face uncertainties, we claim that this problem is especially severe in the context of climate damage modelling. Damage models may be used as tools for exploring qualitative relationships which are too complex for analytical solutions, and for getting a sense of the orders of magnitude of various choices and assumptions (Hael, 2017). They are "inherently heuristic and aim to help thinking and learning about selected traits of the systems under study and their interactions, as well as for performing what-if analyses. When modelling these systems, large simplifications and idealizations are made, information is incomplete or fragmented, and deep uncertainty is characteristic. Full fitting of these models, as well as their evaluation or verification, is hardly possible." (Estrada et al., 2019, p2). Therefore, model results must not be taken at face-value. Damage models provide insights rather than precise estimates. With this caveat in mind, damage models are nevertheless a useful tool to support the policy discussion:

- They are a documented quantitative tool to analyse the SCC in a coherent and consistent way and to make assumptions and approaches transparent.
- For specific input requirements, they provide SCC estimates as well as estimates of global or regional economic costs, and how these evolve with time.
- They allow to analyse a large number of possible scenarios for uncertainty assessments.
- They are a valuable tool helping policymakers to provide a price tag on GHG emissions, which is a crucial part of any climate policy (see further Section 19.4).

Part 3: Mitigation costs

This part of the study focuses on mitigation costs and is structured as follows. Section 16 provides background information on climate change mitigation related aspects in broad such as different interpretations of mitigation costs and an overview on approaches for assessing mitigation costs. Section 17 focuses on mitigation costs for long-term transformation pathways, first outlining the structure of the analysis and providing an overview on the relevant influencing factors for the mitigation costs side, and then analysing these influencing factors in detail in the subsections 17.4.2 to 17.4.11. Section 17.5 provides a summary of the model behaviour of selected models (those used in the ADVANCE database). Section 17.6 discusses selected mitigation cost analysis with a focus on the EU or Germany.
Section 18 summarises the findings of the part on mitigation costs.

16 Background on climate change mitigation

Climate change mitigation refers to actions or measures that reduce the amount of greenhouse gases (GHG) released into the atmosphere, e.g. by reducing fossil fuel combustion, or increase the capacity of carbon sinks to absorb greenhouse gases, e.g. by afforestation. Taking these measures is generally associated with some form of costs as they usually involve active changes to the status quo, e.g. a transformation of the energy sector, implementation of policies, and behavioural changes. The associated costs to achieve GHG emission reductions are called 'mitigation costs'. Alternative terms used in the literature are climate change 'abatement costs' or 'avoidance costs'. As mitigation costs are also related to how the mitigation is achieved, the box below provides some background on different policy instruments for climate policy.

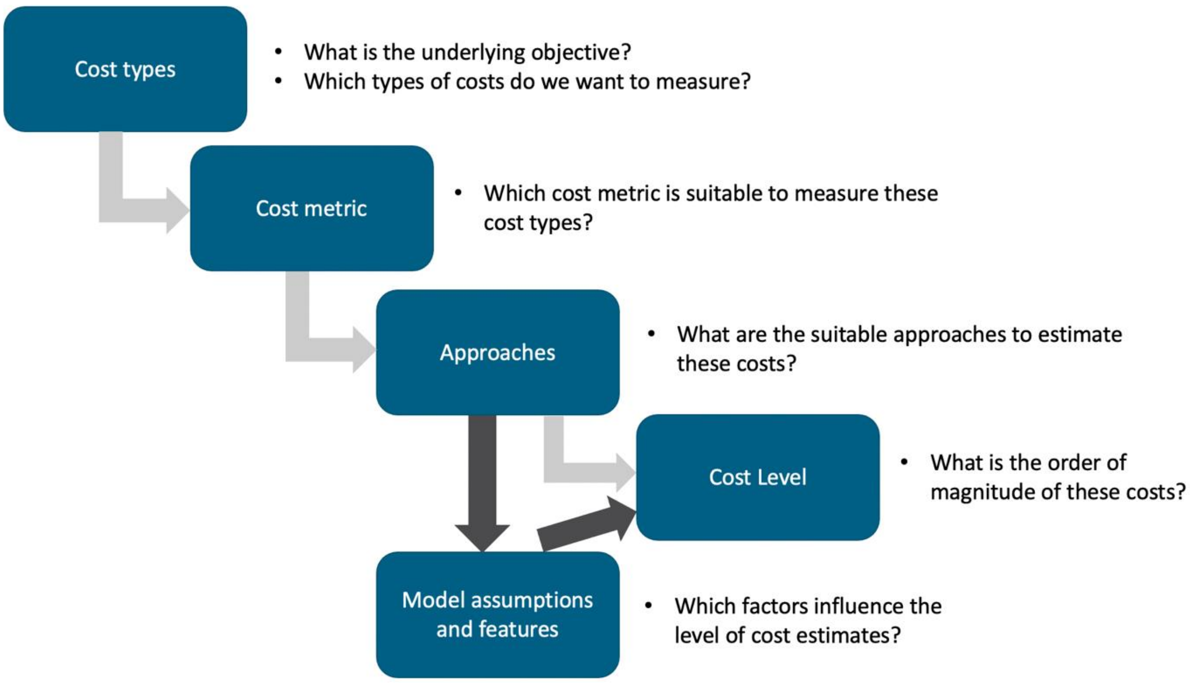
► Mitigation costs as understood in this report:

- do not include costs for adaptation
- focus on the costs of mitigation measures without accounting for the benefits of avoided damages that result from these mitigation measures[158] (these damage costs and adaptation costs are discussed in detail in Chapter 3)

In the literature and political debate, the term 'mitigation costs' is interpreted in diverse ways and can comprise very different cost concepts. Costs accrue at different level of the economy, and different cost assessment approaches focus on different cost types.

Figure 50 provides on indication of the different steps one has to go through to identify which mitigation costs are relevant for the given purpose and how these need to be interpreted.

Figure 50: Steps to identify relevant mitigation cost estimates



[158] When interpreting the presented mitigation cost estimates, it is important to keep in mind that the achieved mitigation is associated with avoided damages that may partly or even fully outweigh mitigation costs.

Source: own illustration, Climate Analytics.

An assessment of mitigation costs requires a careful understanding of:

- which cost types are accounted for in the respective estimate,
- which disaggregation level of cost measurement is chosen, including the perspective and reference point,
- how mitigation costs are measured,
- what the underlying policy or research objective is,
- which assessment approach and model structure are chosen,
- what are the underlying assumptions the estimates are based on.

The following Section 16.1 provides a broader overview of the different types of mitigation costs, disaggregation levels and cost metrics for mitigation costs. Moreover, it identifies different objectives what mitigation costs estimates can be useful for and provides on overview on different approaches that have been used in the literature to assess mitigation costs.

With assessment of the costs of achieving a long-term mitigation target as the most relevant objective for this report, Section 17 focuses on mitigation costs for long-run mitigation pathways. It goes into detail on model structures and the underlying assumptions of approaches that are suitable for long-term mitigation costs assessment. This includes short summaries of selected studies focusing on EU or Germany-specific analyses.

Section 17.6.3.1 summarises the main finding for the mitigation cost side.

16.1 Overview on interpretations of ‘mitigation costs’ and diversity of cost types

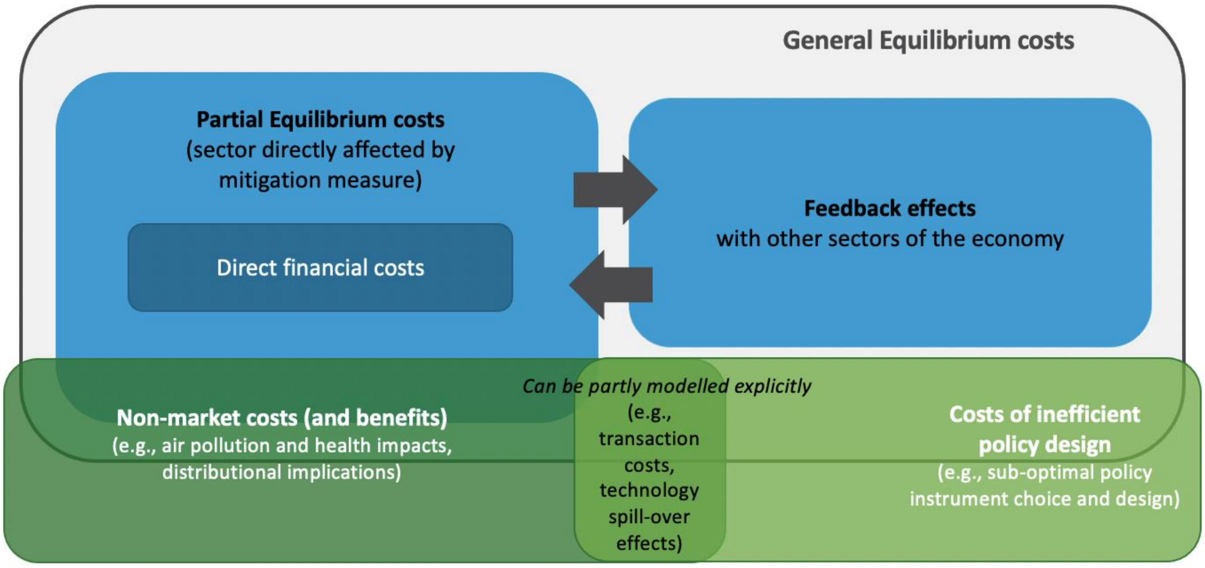
16.1.1 Cost concepts

It is important to differentiate which types of costs are included in the analysis. From a perspective of policy making, the relevant aspects are not only estimating the total costs of emission reductions but also getting an understanding of the *net costs* of mitigation, i.e. the costs of emission reductions accounting for any positive (or negative) side effects of achieving these emission reductions. Different mitigation cost concepts provide insights into different details and cost perspectives, however capturing all different kinds of costs and benefits related to climate change mitigation is a challenging task and there is a gap of the level of information necessary for informed policy making and the type of information any economic analysis can supply (Cooper et al., 1996).

Various typologies for describing the different mitigation cost types have been proposed in the literature. Extending a categorization of economic cost types from the IPCC’s Second Assessment

Report (Cooper et al., 1996) by Hourcade et al.[159] (1996), Söderholm 2012 distinguishes five types of costs related to climate change mitigation: 1) direct compliance costs, 2) partial equilibrium costs, 3) general equilibrium costs, 4) non-market costs and 5) the cost of inefficient policy design. Assessing the costs of the German 'Klimaschutzplan' Öko-Institut e.V. et al. (2019) highlight that the costs of climate change mitigation policies can be differentiated into i) direct economic implications resulting from the implemented policy for the respective sector (linking closely to the partial equilibrium cost category), ii) direct and indirect macro-economic effects on other sectors including induced effects resulting from changes in aggregated demand (describing general equilibrium costs), iii) social impacts and distributional implications[160] affecting households, iv) external costs[161] (and benefits) other than benefits from avoided climate change that result from environmental impacts avoided or newly created, with the iii) and iv) describing non-market costs. Based on these typologies from the literature, in this study we differentiate between the mitigation cost groups described in the following. Note that cost types are not mutually exclusive and can overlap (see Figure 51).

Figure 51: Conceptual illustration of cost types and interrelations



Note: The depiction is only indicative, relative sizes should not be interpreted as reflecting proportions.
Source: own illustration, Climate Analytics.

16.1.1.1 Direct financial costs (direct compliance costs and engineering costs)

These are the costs entities that are affected by the policy face as a direct result of complying with the policy (Söderholm, 2012). It covers the costs of implementing specific technical measures, such as switching from coal to clean energy technologies or planting trees but also benefits from energy savings. Costs are usually measured in Present Value terms and represent the lifecycle costs of a project or technology. Net costs may be negative if the resulting energy cost savings outweigh the technical investment costs (Cooper et al., 1996).

[159] See Chapter 8 of the Second Assessment Report of the IPCC (SAR) „Estimating the costs of mitigating greenhouse gases" by Hourcade and co-authors.

[160] E.g. in case different groups are affected in different ways, increasing for instance social inequality.

[161] E.g. positive or negative impacts on the environment, biodiversity or human health.

16.1.1.2 Partial Equilibrium costs

These include the costs falling under 'direct compliance costs' as well as indirect costs for firms, government and households. Examples for indirect costs are adjustment costs such as administrative paperwork, loss in flexibility or additional time needed for processes. It can also cover costs for government agencies related to enforcement and monitoring of the policy (Söderholm, 2012). Partial equilibrium costs tend to assume that the impact of the policy focuses on one part of the economy, e.g. the sector targeted by the policy, and generally assumes that other sectors remain unaffected. This means that feedback effects and spill-over effects on other parts of the economy are usually disregarded in partial equilibrium cost estimates.

16.1.1.3 General Equilibrium costs

These aim at assessing the costs for the economy as a whole. This means that they additionally account for impacts that a sector-specific policy has on other sectors. In addition, it accounts for feedback effects onto the originally targeted sector as the economy adjusts to the new equilibrium. In case a carbon tax is implemented in the electricity sector, this will directly affect the costs of electricity from fossil fuels, but the absolute and relative price changes will also affect demand and supply in other sectors using electricity as an input. Moreover, other industries further down the supply chain, such as businesses that provide inputs to the coal industry, are also affected, which can in turn have implications on the job market. Representing linkages and interactions between sectors, the general equilibrium perspective allows to provide a more comprehensive picture assessing the economy as whole, which are disregarded in the partial equilibrium perspective. However, due to the high complexity of modelling interlinkages, general equilibrium perspective typically comes along with a more stylised representation of the economy to reduce complexity, partly leading to a lack in detail on accurately representing costs from an engineering perspective. On the other hand, general equilibrium costs help avoiding double counting by aggregating costs over the whole economy (see Section 16.1.3 on 'Measuring costs').

16.1.1.4 Non-market costs (or benefits)

The before-mentioned costs focus on costs that are reflected by markets. However, changes in GDP or consumption may not adequately reflect changes in welfare or well-being, as changes in consumption may not linearly correlate with welfare changes (see Section 5) and other non-monetary impacts as well as distributional aspects are not reflected. These other costs (and benefits) are not accounted for in market-based cost assessments if not modelled explicitly:

- *Non-monetary impacts on households and distributional implications*. Households are likely affected differently by different mitigation cost measures. However, these social costs tend to be disregarded by the market. For example, costs (or benefits) such as a loss in comfort or leisure time of taking public transport or biking instead of driving with one's own car, health benefits from biking, or psychological costs of being unemployed are costs that are not covered by the market. The social cost of rising inequality (or the benefit of reduced inequality) or intergeneration justice also falls under this cost category.
- *Co-benefits.* Climate change mitigation actions can have a variety of implications for other policy areas. The term 'co-benefits' is often used to describe benefits from mitigation that go beyond the direct benefits of reducing damages from climate change. Such co-benefits can include reductions in local air pollution and acid rain (and the resulting health benefits or benefits to crops), improvements in terms of energy security or other economic, social or

environmental effects (Kolstad et al., 2014). While co-benefits in terms of (positive or negative) impacts on employment are often included in partial (employment impacts in same sector) or general equilibrium cost (employment in other sectors), other co-benefits e.g. in terms of avoided environmental and health impacts stemming from air pollution are disregarded in models that do not explicitly account for non-market costs and benefits (see also Box on 'negative costs').

16.1.1.5 Costs of inefficient policy design

From an economic perspective, climate change is a negative externality, imposing social costs that are not reflected by the market price of activities contributing to climate change. Compared to other environmental externalities, the global nature and long-term perspective of climate change complicates the analysis of costs.

According to economic theory the cost-effective way to internalize this global negative externality, requires that marginal costs of mitigation are equal in all places and over all activities. This could be achieved by a uniform economy-wide (global) carbon price[162]. Assuming otherwise perfectly functioning markets, market mechanisms would then take care of finding the most cost-effective (i.e. least-cost) way of reducing CO_2-emissions (Gillingham & Stock, 2018). Mitigation cost estimates that are based on optimization approaches and idealized conditions can thus be seen as a lower bound estimate reflecting the lowest level of costs that could be achieved under otherwise ideal conditions. Deviations from these ideal conditions result in higher mitigation costs.[163]

Two sorts of costs may arise due to sub-optimal policy choice:

- *Deviations from the least-cost policy*. While a uniform (global) carbon price would be desirable from the perspective of economic theory, we observe that the political reality of climate change mitigation looks very different. Climate change mitigation policy is usually a patchwork of different policies targeting different sectors and technologies. As a consequence, in reality, mitigation costs for different mitigation options differ. Mitigation costs vary depending on the technology and the sector under consideration if the design of the mitigation policy does not allow costs to adjust[164] or additional market failures persist. As long as marginal abatement costs differ between sectors or countries, there is potential to reduce the costs, i.e. there are additional costs of choosing an inefficient policy (Söderholm, 2012). Policy instrument choice and policy design can thus substantially drive the associated mitigation costs. Note, however, that interactions with pre-existing policies can also affect overall mitigation costs (e.g. other environmental taxes).
- *Conflicting short- and long-term least cost options.* The long atmospheric lifetime of CO_2 (and other GHG) requires taking a long-term perspective and an intertemporal optimization approach to identify the least-cost mitigation pathway over time. In the literature some mitigation cost estimates take a static perspective, describing the costs for a 'snapshot' in time, e.g. the (expected) costs for a specific year in the future. While these measure-explicit

[162] The term "carbon price" typically refers to all GHG emissions, not only CO_2. Alternatively, the term 'emissions price' is also common in the literature.

[163] Assuming the absence of other market distortions that need to be corrected.

[164] See e.g. Box 12 on different policy instruments for mitigation.

marginal abatement cost curves, which are mainly static, can provide useful (often detailed) information on which policy options are the best mitigation options based on today's technology, they can be misleading with regard to designing optimal emission reduction strategies for the long-run (Vogt-Schilb & Hallegatte, 2014). Due to high inertia, least-cost long-term mitigation strategies may instead require (i) implementing more expensive mitigation options before the whole potential of currently cheaper options has been exploited; (ii) use more expensive options even when less expensive options seem sufficient to meet the climate target; or (iii) start the implement action of some more expensive options even before cheaper ones. Vogt-Schilb and Hallegatte (2014) show for instance for the EU, in order to reach long-term target of the -75% by 2050 the best strategy may be to start with implementing some more costly, but high potential options that require longer time to be implemented (Vogt-Schilb & Hallegatte, 2014). In contrast, relying on the currently cheapest mitigation cost options to achieve the short term goal of –20% by 2020 risks creating a lock-in and rendering the long-term (2050) target more expensive.

Box 11: Policy instruments for climate change mitigation

Apart from voluntary behavioural changes of businesses and households (e.g. switching to a low-meat diet or reducing air travel), policy makers have a broad set of policy instruments available that can be applied to achieve emission reductions. These include:

- *Economic incentives:* price instruments such as taxes, subsidies, emission trading
- *Direct regulatory approaches ('command-and-control'):* e.g. emission standards, prohibitions/bans)
- *Information and information design:* e.g. awareness raising campaigns, education on risks from climate change and which actions are associated with high carbon emissions, nudging
- *Voluntary approaches:* e.g. voluntary standards/guidelines, self-certification

Economic incentives are considered more cost effective (i.e. have lower mitigation costs) than direct regulatory interventions due to market forces exploiting least cost options. Economic theory suggests a global uniform emission price[165] to be the least-cost option. However, economic theory often abstracts from transaction costs for implementing policies. Depending on the policy design, transaction costs for pricing policies (especially emission trading) can be high.

The mitigation costs associated with a specific emission reduction target therefore also depend on the chosen policy instrument to achieve this target. Moreover, the true performance of a policy instrument depends on a range of factors, including institutional capacity, uncertainty and pre-existing conditions (e.g. other market failures or culture) and other aspects such as political feasibility (see Box 12).Interactions between different policy instruments, e.g. pre-existing taxes or regulations, can influence effectiveness and mitigation costs as well (Kolstad et al., 2014).

[165] In the case of certainty, i.e. complete knowledge also about future developments, price-based (i.e. an emission tax) and quantity-based (i.e. a cap and trade scheme) instruments are equivalent. However, under uncertainty regarding damage and mitigation costs, price-based instruments are better if mitigation costs are more uncertain than damages costs and vice versa (Weitzman, 1974). Different hybrid approaches e.g. Emission Trading Schemes with price ceilings and price floors have been implemented (Kolstad et al., 2014).

16.1.2 Disaggregation level and perspective chosen

16.1.2.1 Disaggregation level of the cost analysis

Cost estimates can for example refer to *different levels of geographical disaggregation*, such as local level, country level, larger region (e.g. Europe, OECD) or world.

Additional to differences in the cost concept and regional focus, it is important to note that there are different disaggregation levels beyond spatial disaggregation that mitigation cost estimates can refer to (see Table 20).

Table 20: Potential disaggregation levels for mitigation cost analysis

Level	Description	Cost type and examples	Methodological frameworks (e.g.)
Project (or measure)	**Focus on a 'stand-alone' measure** that is assumed to not affect markets and prices.	Mainly direct financial and engineering costs: E.g. Implementation of a specific technical facility, infrastructure or regulation measure such as technical standards or demand-side regulations	• Cost-benefit analysis (e.g. performed by businesses) • Cost- effectiveness analysis • Lifecycle analysis
Technology	**Focus on a specific technology for GHG emission reductions**, typically with applications in several sector and projects. Generally focused on **technical characteristics and learning curves**.	Mainly direct financial and engineering costs: E.g. Technology costs and projected cost developments	Similar to level "project"
Sector	**Focus on assessing costs for sectoral policies in a partial equilibrium framework**	Partial equilibrium costs (see Section 16.1.1.2). Non-market costs can be modelled explicitly. Mitigation policies assessed can range from economic instruments (e.g. taxes, subsidies) to demand side regulations or the implementation of large-scale investment projects.	• partial equilibrium models • technical simulation models for specific sectors
Macro-economic	**Assesses the costs of climate change mitigation measures across the economy as a whole**, i.e. taking interaction effects between different sectors into account	General equilibrium costs (see Section 16.1.1.3). In contrast to sector-level includes feedback effects on other sectors. Non-market costs can be modelled explicitly. Polices analysed range from implementation of economic instruments to specific investment programmes or technology and innovation policies, including economy-wide policies.	Macro- economic models, such as • general equilibrium models • Keynesian econometric models • Integrated Assessment Models (IAMs)

Level	Description	Cost type and examples	Methodological frameworks (e.g.)
Society	**Assessment of mitigation costs beyond direct economic costs.**	Can include second-order effects and non-market costs, such as distributional impacts, energy security, affordability of electricity, health implications (see Section 17.4.9)	• Impact Assessments • Multi-Criteria-Analysis • Qualitative analysis

Source: Table content derived based on AR4, WGIII Chapter 2 (Halsnæs et al., 2007) and extended by Climate Analytics.

16.1.2.2 Perspective – Who pays which costs?

Another important point of reference is the *perspective of who is facing the respective costs*, e.g.

- businesses taking investment decisions, or being affected by a policy,
- the government assessing the implementation costs of a certain mitigation measure (e.g. for its budgetary planning) or assessing the costs to the economy,
- consumers or more generally households,
- the society as a whole,
- certain groups (specific sectors, population groups, future generations).

It is important to differentiate between *private costs,* measured from a private perspective and *social costs,* measured from the perspective of the society as a whole. Private costs are borne by an individual or a business. However, actions of individuals can cause external costs to society, such as environmental costs, which the individual does not take into account in its own decision making. Climate change is also such a negative externality, air pollution from fossil fuel combustion or increased social inequality are other examples. The 'social costs' combine these external costs and the private costs (Halsnæs et al., 2007).[166] Cost assessments that take a specific perspective, e.g. the perspective of a business, may only account for costs that have to be borne by this business and neglect costs to other actors or costs to society.

Related to this is the differentiation between *social cost* (see above) and *financial costs* – or more generally the *economic perspective on costs* is different from the *perspective of financial accounting* (Söderholm, 2012): Costs in financial accounting have a narrow perspective, largely limited to direct financial expenses (including depreciation for capital equipment) e.g. from the perspective of a business making investment decisions. Moreover, this 'engineering costs'-view focuses on costs that are attributed to the technology and tend to disregard the social and economic context in which this technology is applied (Söderholm, 2012). It furthermore tends to have a static perspective, disregarding potential spill-over effects or long-term dynamics resulting from induced changes (Gillingham & Stock, 2018). The economic perspective on costs,

[166] Note that for damages costs we defined the Social Costs of Carbon as the discounted sum of future climate damages caused by emitting one additional ton of CO_2. There is no explicit reference in this definition to private costs, as emissions do not cause any private costs.

in contrast, can comprise a variety of different cost types beyond financial expenses, including indirect impacts (see Section 16.1.1).

Another important consideration is the **distribution of the costs**, e.g. if certain groups on the population face a higher cost burden than others. The least cost-option may thus not always be the preferred option from a political perspective, as distributional issues and related political feasibility aspects need to be taken into account (see Box 12). Also related to this is the question of burden sharing/effort sharing not only within but also between countries or regions. These equity questions involve value judgement, as is discussed in more detail in Section 17.4.5.

Moreover, the long-term optimization problem also leads to ethical questions on **intergenerational justice** as discussed in detail in AR5 Ch. 3 (Kolstad et al., 2014). When the burden of mitigation costs is shifted into the future – for example by applying high discount rates – future generations that have not been responsible for the majority of the GHGs accumulated in the atmosphere will need to face both higher mitigation costs as well as higher damages from climate change (see Section 17.4.4).

Box 12: Evaluation criteria for mitigation policy

Minimising mitigation costs may only be one objective of decision making. The Fifth Assessment Report of the IPCC identifies four 'evaluation criteria' for policy choice (Kolstad et al., 2014, p. 3):

1. Cost effectiveness and economic efficiency: The level of associated mitigation costs.
2. Environmental effectiveness: The extent to which emissions are actually reduced and the mitigation target is achieved.
3. Distributional effects: How impacts are distributed between different subgroups.
4. Institutional and political feasibility: Whether the administrative burden is manageable and the policy is likely to gain political support and be implemented.

These evaluation criteria are interlinked. Political feasibility may be influenced by distributional considerations, as well as overall cost effectiveness. In turn, environmental effectiveness may be affected by political feasibility concerns.

16.1.3 Measuring mitigation costs

16.1.3.1 Overview on common cost metrics

A multitude of different metrics to measure mitigation costs can be found in the literature, often measuring very different types of costs. There is no single ideal metric for reporting mitigation costs available, and different cost metrics are often not directly comparable (Krey et al., 2014).

Project-level or technology-specific cost assessments typically provide an estimate for the total costs implementing the mitigation project (e.g. implementing a wind park) or installing a single unit of the technology (e.g. costs per wind turbine) assessing life-cycle costs.

Common mitigation cost metrics in studies that assess macro-economic costs are Changes in Gross Domestic Product (GDP) or Changes in Consumption. For sector-specific costs, one common metric is Additional Energy System Costs. Investment costs are also commonly reported.

The mitigation costs measured by the Area under the Marginal Abatement cost curve (Area under the MAC) is another cost metric commonly reported for both, macro-economic or sector-specific analyses.

Another typical metric commonly reported for both, macro-economic or sector-specific analyses is the Carbon Price or Emission Price. The term Carbon Price frequently refers to all GHGs and not just CO_2 emissions.

For a more detailed discussion of cost metrics for assessing long-term transformation pathways and the importance of differentiating between total, average and marginal costs see Section 17.4.2.

16.1.3.2 Reference point and timing of analysis

Costs compare to what? Several of the aforementioned cost metrics (e.g. change in GDP, change in consumption) are measured as relative costs meaning that they cannot be measured without comparing changes to a certain *reference point – a so-called baseline or benchmark* (Söderholm, 2012). The role of the baseline will be discussed in detail later (see Section 17.4.3.2).

Timing of the analysis: Related to the question on the reference point is the question whether cost estimates result from an ex-post or ex- ante perspective (discussed in more detail in Section 16.2.2.3):

- *Ex-post analysis*: quantifying mitigation costs of measures or polices that have already been implemented, mainly exploiting observed data.
- *Ex-ante analysis:* Projecting costs for planned or potential future mitigation actions, mainly relying on projections and assumptions about future developments, adding the role of uncertainty to the analysis.

Box 13: Can mitigation costs also be negative?

The literature suggests that some mitigation opportunities are associated with negative costs, i.e. the benefits from carrying out the mitigation action outweigh the costs (Kolstad et al., 2014, p. 3).

A *negative private cost*, i.e., for a business or household, implies that the pursuit of self-interest, i.e. maximization of own utility as assumed in economics, has not been fully carried out. Reasons for this are institutional, political or social barriers (e.g., informational costs, time constraints, risk aversion). Especially engineering-focused studies tend to point to these “negative cost opportunities”. However, idealized assumptions can lead to an overestimation of such negative costs, among other things due to a rebound effect (i.e., people spending the money saved through energy efficiency measures on other carbon intensive activities) or due to existing barriers such as administrative costs or lacking information keeping actors from exploiting these presumably negative cost mitigation potentials.

Negative social costs, i.e., social benefits from mitigation (excluding avoided climate change damages), can arise if private decision makers do not take negative externalities of their own action on others into account. This relates to the discussion on co-benefits, where e.g. the literature suggests that the benefits of reducing the health impacts from air pollution caused by fossil fuel combustion could outweigh mitigation costs in certain regions (Markandya et al., 2018).

16.2 Overview on decision-making objectives and methodological approaches for mitigation cost assessment

16.2.1 Stakeholders and decision-making objectives

Mitigation costs estimates are relevant for different *stakeholders,* ranging from policy makers to scientists and researcher, to businesses and private investor or consumers, to voters and to advocacy groups such as NGOs, philanthropic organizations and lobby groups and multilateral organizations (like the GCF or the World Bank) (see Box on 'other stakeholder groups'). Moreover, mitigation costs estimates can serve various purposes and *decision-making objectives* which can differ between those stakeholders.

Policy makers need to understand the costs related to climate change mitigation to be able to take informed decisions on climate policy implementation. There are various decision-making objectives for policy makers (in the following called 'Policy questions') where mitigation cost estimates can be relevant (see Figure 52):

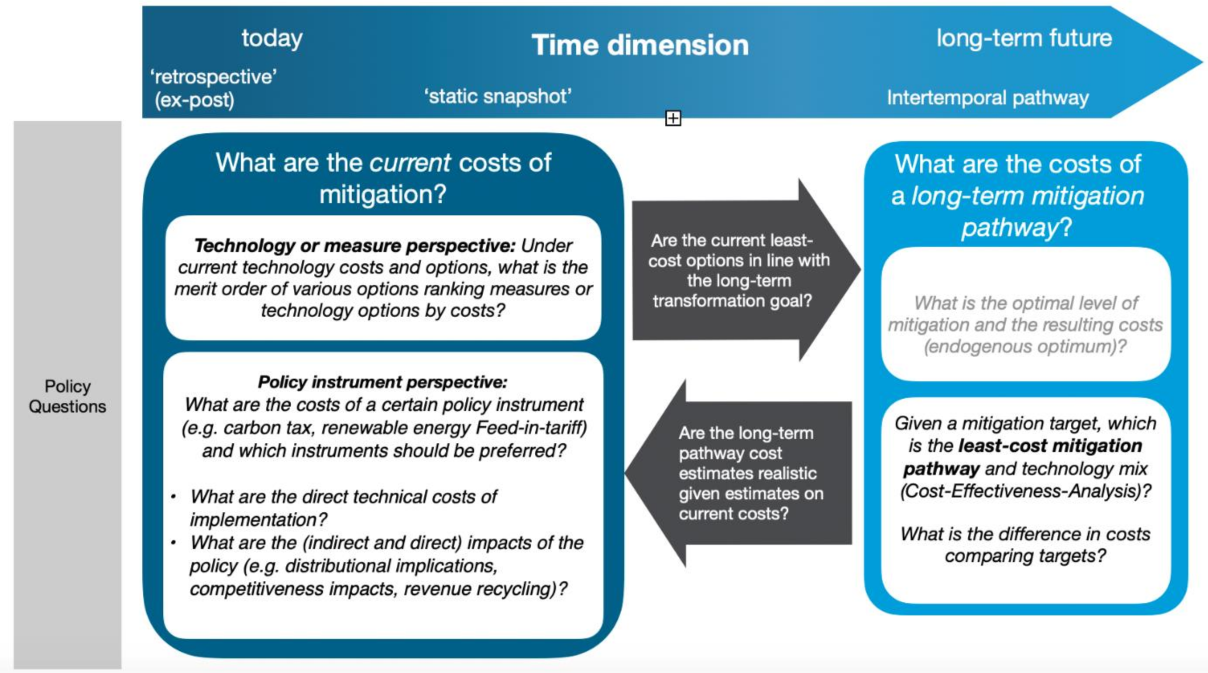
- *Mitigation target perspective: Assessing the costs of achieving a (long-term) mitigation target*
  - Cost-Effectiveness Analysis: Identifying the least-cost pathways for achieving a pre-defined global mitigation target such as the Paris Agreement long-term temperature goal or national (or EU-wide) mitigation targets outlined in the NDCs or national level climate strategies. Results can provide benchmarks for socially valuable mitigation measures (private and public) and climate policy instruments and can be used to justify or define tax rates to reach the pre-defined (sector-specific) emission target.
  - Cost-Benefit-Analysis: Identifying the optimal climate mitigation target by weighing costs of mitigation against benefits of avoided damages from climate change (see Section 10)
  - Can also provide information on least-cost technology mix over time.
- *Technology or measure perspective: Assessing the (current) technology costs and options.*
  - Identifying the 'most promising' least-cost measures (e.g. energy efficiency, insolation of buildings) and technology options (e.g. solar PV).
  - Typically, a static analysis with focus on short- to medium-run (see 'mitigation target perspective' for assessing least-cost technology mix over time)
  - Analysis typically does not go into detail on suitable policy instruments or instrument design, however, can be used to derive insights for how policy making can support the exploitation of these mitigation options, e.g., by implementing investment policies or subsidies for renewable energy technologies.
- *Policy instrument perspective: Assessing the costs related to a certain policy instrument and instrument design.*
  - Policy makers can be interested in assessing the costs of a policy instrument (e.g. renewable energy subsidy, carbon tax, energy efficiency standard; see Box 11) that has

already been implemented (ex-post impact analysis) or assessing the (expected) costs of instruments that are proposed to be implemented (ex-ante analysis).

- Can include assessing the implementation costs, e.g. the administrative costs and the costs to remove barriers as well as the impact on the economy or certain groups (e.g. sectors, population groups).
- Can include comparing different options for the design of an instrument (e.g. with regard to different revenue recycling schemes of a carbon tax/ levy) e.g. with regard to distributional implications of the policy instrument.

The perspective of the stakeholder as well as the reference level are decisive for the type of mitigation costs that are of interest for this specific decision-making objective. Comparing mitigation costs estimates that refer to different underlying decision-making objectives can be misleading. Figure 52 illustrates that for example the time perspective for the underlying policy questions can be very different, complicating a direct comparison of costs.

Figure 52: Conceptual illustration of the time perspective of different policy questions



Note that the figure intends to illustrate the general tendency, acknowledging that exceptions exist.
Source: own illustration, Climate Analytics.

► **Main interest of this report chapter is in assessing the mitigation costs related to long-term mitigation pathways to achieve a pre-defined mitigation target (Mitigation target perspective applying Cost-Effectiveness-Analysis)**

Box 14: Other stakeholder groups with interest in mitigation cost estimates

While the main focus of this report is on the perspective of policy makers, we give a brief overview on other stakeholder groups and their potential interests in mitigation cost estimates:

- *Businesses and private investors* need to understand mitigation costs to plan investment decisions and anticipate policy decisions e.g. with regard to future regulations. Their interest is mainly in the direct financial costs or investment costs related to climate change mitigation. This includes broader market (potential) analyses or technology-specific analyses focusing on the cost of a certain technology. This can be e.g. analysing the implementation costs of building a wind park or analysing the cost development in carbon capture and storage (CCS) projects. Investors are likely interested in projected emission prices.
- *Researchers and Scientists* may on one hand side conduct mitigation cost analysis to provide scientific advice to policy makers and on the other hand side to improve the scientific understanding of climate change mitigation and the resulting costs. Approaches found in the scientific literature are very diverse and depend on the specific research question.
- The *general public and advocacy groups*: Voters, taxpayers and more generally the public want to receive a basis for decision making regarding political preferences in elections. Similarly, advocacy groups want to understand whether their particular concerns (such as employment impacts, equity and social development concerns or environmental concerns) are reflected in current and planned climate policy implementation.

In the following, different approaches that are commonly used to assess mitigation costs are introduced.

16.2.2 Overview on approaches to assess climate change mitigation costs and discussion of their general strengths and weaknesses

Economic tools can provide useful insights for determination and designing mitigation actions and assessing the positive and negative implications of climate change mitigation options. However, all economic tools and methods have their strengths and limitations and need to make simplifying assumptions which need to be kept in mind when interpreting the results. No method can be considered the single best method, and no method by itself can provide a comprehensive analysis (Kolstad et al., 2014). A combination of methods is generally needed to grasp the broader implications, trade-offs and complexities of mitigation policies.

A variety of approaches for assessing climate change mitigation costs have been used in the literature. Based on the literature as well as reviews on climate change mitigation costs (Huang et al., 2016b; Isacs et al., 2016a; Kok et al., 2011; Sathaye & Shukla, 2013), IPCC Assessment Reports (Fifth Assessment Report (AR5) (Edenhofer et al., 2014) and the Special Report on 1.5°C (SR1.5) (Masson-Delmotte et al., 2018), review articles (Gillingham & Stock, 2018; Isacs et al., 2016b; Rosen & Guenther, 2015; Sathaye & Shukla, 2013) as well as different meta-analyses (Barker et al., 2002; Kuik et al., 2009b; Vermont & De Cara, 2010), we identify different clusters of approaches and discuss their main characteristics as well as strength and limitations. A more in-depth review of selected approaches can be found in Section 16.2.2.3)

16.2.2.1 General concepts for decision making and framing the analysis

Before going into methodological approaches, it is important to understand differences in the general concept and framing of the analysis.

The Third and Fourth Assessment Report of the IPCC identified three main types of 'decision support tools'[167] (Halsnæs et al. 2007; Stocker et al. 2001)

- Cost-Benefits Analysis (CB) [168],
- Cost-Effectiveness-Analysis (CE) and
- Multi-Criteria Decision Analysis (MCDA)[169].

A major difference between these three is how they bring together different costs and benefits including the question in how far monetary values are used to reflect the considered impacts and derive an overall (aggregated) value (Halsnæs et al., 2007).

Cost-Benefit-Analysis aims at directly weighing costs against benefits and therefore needs to assign monetary values [170] to the full range of costs and benefits accounted for, which can be challenging (see also Chapter 2 and Box 2). While one advantage of the integrated modelling of climate impacts and modelling of mitigation costs is that it allows CB-IAMs to capture the feedback from climate response to socio-economic damages in an aggregated manner, an important drawback of CB-IAMs, however, is that they are usually much more stylised than detailed process IAMs used for Cost-Effectiveness Analysis and are often criticized for containing limited depth (Rogelj, Shindell, et al., 2018) (see also Section 2.1. Models that represent both, the damage cost side as well as the mitigation cost side, are briefly discussed in Section 10 which deals with damage cost perspective. The general concept of directly weighing costs against benefits is often applied in a business-related context for taking investment decisions. In the context of climate change, CBA refers to weighting the costs of climate change mitigation against the benefits of avoided damages from climate change. This leads to two important assumptions (Halsnæs et al., 2007):

1) That it is possible to compensate between the different values of impacts on benefits and costs expressed in monetary terms (e.g. that lower mitigation costs can compensate for higher climate damages).
2) That such monetary compensation values can be defined also for all involved non-market values such as air pollution, health impacts and biodiversity.

Multi-Criteria Decision Analysis (or Multi-Attribute Analysis), in contrast, aims at bringing different decision-making parameters into a common analysis framework without forcing a common (monetary) unit on all of them. The different dimensions (impacts) are identified and are transparently assigned with weights (e.g. through a stakeholder consultation or expert panels or explicit assumptions). Both, quantitative and qualitative information can be used. Options can be compared by developing a scoring leading to a ranking. As such, Multi Criteria Decision Analysis is a general framework (umbrella-term) for complex decision making with multiple often conflicting objectives that are valued differently by different stakeholders (Heli

[167] The Fourth Assessment Report moreover names a range of other tools, such as tolerable windows/ safe-landing/guard-rail approaches, game theory, portfolio theory, public finance theory, ethical and cultural prescriptive rules, various policy dialogue exercises and green accounting.

[168] See also Section 10

[169] The Third Assessment Report used the term Multi-Attribute Analysis, but Multi-Criteria Decision analysis is generally considered the more general term for this type of decision-making approach.

[170] Typically, market prices are used for valuing costs. For some costs it is however not possible to derive a monetary value based on market prices or the market price value does not seem an appropriate measure, e.g. health costs or the valuation of lives lost.

Saarikoski et al., 2016). It can allow a comprehensive analysis of the different types of costs and benefits, especially those that are hard to monetize, e.g. biodiversity loss or health damages, allowing for different valorisation and weighting of different cost and benefits types. But as such it will usually not aim to provide a single aggregate mitigation cost estimate. While Multi Criteria Decision Analysis is helpful in reflecting the complexity and normative character of a complex decision issue such as climate change mitigation, the aim of this report is to compare estimates that quantify mitigation cost (in monetary terms) which necessitates aggregating costs (and benefits) in a common (monetary) number. Therefore, MCDA-based is not the focus of this report. Yet, insights from MCDA type of analyses can be useful to reflect on value judgements in CEA assessments.

By focusing on a pre-defined (exogenously given) target**, Cost-Effectiveness-Analysis** avoids the need to directly weigh avoided damages against mitigation costs. This however leads to the fact that CE-types models do not directly account for climate damages due to delayed mitigation action and temporary overshoots[171] as feedback effects on the climate are not taken into account in the optimization procedure. Imposing additional constraints, such as limiting the maximally allowed overshoot or the maximum sustainable potential of bio-energy with Carbon Capture and Storage (BECCS) can be used to indirectly add damage cost considerations, however, the GDP trajectories or other outcomes of the models will not account for potential climate change impacts.

- ► **Focus of the mitigation cost analysis part in this report are mitigation cost estimates that do not explicitly model damages from climate change, but focus on achieving a pre-defined mitigation target (i.e. Cost-Effectiveness-Analysis).**

Table 21 provides on overview on the main advantages and disadvantages of Cost-Benefit-Analysis, Cost-Effectiveness-Analysis and Multi-Criteria Analysis.

[171] Temporary overshoot means that the long-term temperature goal is met in the long-run (e.g. in 2100), but due to the usage of negative emission technologies that extract GHG emissions from the atmosphere, the mitigation pathway allows to exceed the emission budget associated with the temperature goal temporarily.

Table 21: Main Advantages and Disadvantages of CB, CE and MCDA for assessing mitigation cost rates

	Cost-Benefit-Analysis (CB or CBA)	Cost-Effectiveness-Analysis (CE or CEA)	Multi Criteria Analysis
Advantages	+ takes **damages from climate impacts and costs from mitigation into account**	+ **avoids monetarization of climate damages** + predefined mitigation target can be set by policy makers/public debate	+ allows to combine different cost and benefits types in common framework **without imposing common unit or monetarization** + can help to structure and analyse complex problems
Disadvantages	- Stylized, **simplified** representation - Requires **measuring all costs and benefits in same (monetary) unit**, including non-market costs - Assumes that **climate damages and mitigation costs can be 'traded' against each other**	**- Does not account for differences in damage costs and risks of irreversibility** resulting from temporarily overshooting long-term target **- Does not set the mitigation cost into context with the benefits** of avoided damages	- Does usually **not provide aggregation of costs** needed to derive cost rates

Source: own illustration, Climate Analytics.

Models that assess long-term transformation pathways typical either apply Cost-Benefit-Analysis or Cost-Effectiveness-Analysis. These usually assume the implementation of a carbon price to assess the resulting consumption or GDP losses compared to the baseline scenario. Though the intertemporal optimization accounts for the long-term characteristics and required long-term transformation processes, it usually does not account for 'real-world' barriers (e.g. transaction costs, other market imperfections), policy implementation costs as well as institutional, organisational and behavioural barriers related to the actual implementation of the climate policy. The costs of inefficient policy design are not accounted for either (Söderholm, 2012).

16.2.2.2 Impact Assessments

Another common approach to structure and to define the framing of an analysis assessing the costs of a mitigation measure are **Impact Assessments**. Impact Assessments typically take the perspective of estimating the effect of a specific policy or measure/policy instrument. They typically aim at capturing 'real world barriers' and implementation conditions and resulting costs.

There are different types of Impact Assessments. One important distinction is whether they evaluate the cost of a specific policy *ex-post*, i.e. focusing on the mostly empirical analysis of an implemented policy or *ex-ante,* i.e. making projection on the expected effect of a proposed policy. Impact Assessment can make use of different underlying decision frameworks (e.g. applying Cost-Benefit-Analysis, Cost-Effectiveness-Analysis or Multi-Criteria Analysis or even a combination). Moreover, the nature of underlying methodologies can be very diverse, ranging from modelling to econometric analysis, to descriptive or even qualitative analyses, or again, a combination of different methodologies. Moreover, the type of authors and target audience can differ: Impact Assessments are common in the scientific literature as well as to assess the impacts of potential laws or policy instruments ('Gesetzesfolgenabschätzung') in the political process. Impact assessments can have a specific focus (e.g. the impact on competitiveness) or can be a comprehensive assessment of a broader set of different cost types, then usually not aggregating total costs in one number.

Öko-Institut e.V. et al. (2019) for example conduct a comprehensive (ex-ante) impact assessment of the German 'Klimaschutzplan' (Öko-Institut e.V. et al., 2019). Böhringer et al. (2016) do an impact assessment of the EU Climate and Energy Package based on a Computable General Equilibrium (CGE) approach. Liu and Lu (2015) assess the economic impact of different revenue recycling schemes for a carbon tax in China based on a CGE. Yusuf and Resosudarmo (2015) assess the distributional implications of a carbon tax in Indonesia using a CGE. Examples of ex-post assessments using econometric approaches are Martin, Muûls, and Wagner (2016) assessing the impact of the EU-ETS on the competitiveness of regulated businesses as well as Calel and Dechezleprêtre (2014) who investigate the impact of the EU ETS on innovation.

An example of a hybrid between long-term mitigation pathway modelling and impact assessment is the in-depth analysis conducted by the European Commission (European Commission, 2018a), assessing the impact of the EU long term strategic vision for a climate neutral economy. While Impact Assessment typically assess the effects for a specific measure/policy instrument, the analysis by the European Commission conducts a type of impact assessment for a long-term transformation strategy (mainly defining targets without focusing on policy instruments) and not a specific measure. The results of the EU Commission's analysis are discussed in more detail in chapter 17.6.1.1.

16.2.2.3 Modelling perspective - Cost assessment approaches from the Micro– versus Macro-perspective

An important differentiation of approaches in the literature is between **Bottom-up, Top-Down and Hybrid** approaches (Huang et al., 2016a; Isacs et al., 2016b; Sathaye & Shukla, 2013). This differentiation refers to the perspective the model is taking and the related technical detail that is accounted for. The terms 'top-down' and 'bottom-up' modelling are commonly used in the economic and energy modelling context; however, the meaning of these terms is not always clear cut. In top-down economic models macro-level indicators mark the starting point. In contrast, in bottom-up economic models the starting point is the sectoral output then deriving the macro-level results based on the sum of the sectoral level (Cambridge Econometrics, 2019). One important difference between top-down and bottom-up models is the way capital and technology are treated.

This section provides an overview on the different approaches and their main characteristics and strengths and weaknesses. In view of the main interest in this report in assessing long-term mitigation pathways (see policy questions in Section 16.2.3), this section mainly focuses on approaches suitable for long-term pathway assessment, while approaches more suitable for short term assessment or other policy questions are discussed only briefly.

16.2.2.3.1 Bottom-up Models

Bottom-up models usually **provide a highly disaggregated depiction of technological characteristics of mitigation options, looking at certain sectors from the "engineering perspective", while they do not cover a complete characterisation of overall economic activity.** Due to the necessary level of detail, bottom-up approaches usually focus on specific countries or sectors – mainly the energy sector. Capital equipment is modelled explicitly and in detail, e. g. with regard to generating equipment or other energy-related capital or infrastructure (Cambridge Econometrics, 2019).

Commonly used bottom-up models are for example POLES (see Appendix for a brief description) as well as MARKAL[172], TIMES (Loulou et al., 2016) and OSeMOSYS[173] . A long list of open-source models – mainly bottom-up models – with tables comparing characteristics and short descriptions can be found on the OpenMod website[174].

Bottom-up models can be further differentiated in:

- Financial accounting models
- Optimization models

Financial Accounting models

Financial accounting models usually derive a Marginal Abatement Cost curves (MAC-curve) ranking the different cost-effective measures from low (or even negative) to high costs, either based on calculating "break-even abatement costs" or "incremental costs". Vogt-Schilb and Hallegatte (2014) call MAC-curves that provide information on abatement costs and potentials for a set of mitigation measures 'measure-explicit' MAC-curves (as opposed to 'continuous' MAC-curves built on Integrated Assessment models (see section on IAMs)). Vogt-Schilb and Hallegatte (2014) further differentiate between 'full potential' and 'achievable potential' MAC-curves.[175]

MAC-curves can help policy makers to identify technological and non-technological options for abatement, ranking them by abatement potential and unit costs (marginal costs), providing a static snapshot of options and costs. It is important that policy makers are aware of the assumed technical progress that underlies MAC-curves. If a MAC-curve assesses current technology cost only, the mitigation options that are currently the cheapest options may be chosen. This may not be in line with the optimal strategy to achieve long-term mitigation targets as lock-in effects can be created (Vogt-Schilb & Hallegatte, 2014). As 'measure-explicit' MAC-curves provide a static snapshot of options and costs (often centered around specific sectors), which may not be in line with the optimal strategy to achieve long-term mitigation targets, these models are not the focus of this report. Another point to consider is, though representing the costs and abatement potentials of different measures, MAC-curves do not reflect interactions and feedback effect between measures (Vogt-Schilb & Hallegatte, 2014). Moreover, MAC-curves usually assess only direct financial costs for implementation of a project or technology costs and disregard other types of costs such as general equilibrium costs, partial equilibrium costs as well as non-market costs/benefits institutional barriers, transaction costs and non-monetary costs.

One of the most well-known studies using financial accounting is the McKinsey MAC-curve, projecting the 'achievable potential' MAC-curve for the year 2030 (McKinsey and Company, 2009).

Optimisation models

Optimisation models use optimization algorithms to **find the least-cost mix of technologies for a system and a given discount rate subject to technological and environmental**

[172] For a review of MARKAL-based energy modeling see, for instance (Zonooz et al. 2009; Loulou et al. 2004).

[173] For a description of the OSeMOSYS model see (Howells et al. 2011). OSeMOSYS has been employed to develop energy system models at the global level as well as at the scale of continents (African Power Pools, South America, EU28+2) down to the scale of countries, regions and villages. OSEMBE is the European model built using OSeMOSYS, covering the period from 2015 until 2050 (Järvinen & Shivakumar, n.d.).

[174] https://wiki.openmod-initiative.org/wiki/Open_Models (last accessed Nov 24, 2020)

[175] The 'full potential' approach assesses how much emissions could be avoided at a certain point in time if measures were applied at their maximum technical potential and compares these emissions to a reference or baseline technology (accounting for differences in carbon intensity and imperfect substitutability between different technologies). The 'achievable potential' measure-explicit MAC curve aims at assessing the marginal costs for a specific time in the future (e.g. the year 2030). For this, it has to make assumptions on the large-scale diffusion of new technologies and future costs and assesses the mitigation potential (and costs) that could be achieved if the implementation progressed at a given speed.

constraints. They usually present a range of technical details regarding the supply and the demand side, commonly focusing on the energy sector. Such bottom-up models are capable to derive the least-cost technology mix to satisfy a given level of final energy demand under various user-defined, scenario-specific constraints such as emissions constraints. While providing a detailed representation of technological aspects of the energy system, these types of models are capable to assess the implications of various micro-level policy measures, for instance, targeted subsidies or constraints for particular groups of technologies. These can for example be technology-specific policies, which aim to restrict the future investments into specific technologies (e.g. nuclear power plants, unabated coal power plants). At the same time, such models could assess the impacts of macro-level policy measures and targets such as carbon taxes or permit trading systems (Loulou et al., 2016).

However, these **bottom-up models disregard the interactions of the energy system with the rest of the economy, while merely focusing on an explicit representation of the energy system**. Additionally, as no climate module is linked, for implementation of climate stabilization scenarios, in bottom-up models long-term climate targets need to be first translated to cumulative emission budgets or annual emission constraints for the respective modeled sectors. Furthermore, agriculture and land-use systems need to be dealt with exogenously.

General strengths and weaknesses of bottom-up models

Bottom-up models provide technologically feasible and cost-effective mitigation strategies. However, they are incapable to assess further dimensions of feasibility such as political, institutional and social feasibility of proposed decarbonisation pathways. They typically disregard the social and institutional barriers as well as further implementation constraints such as capital constraints or interactions between the energy sector and the rest of the economy and the impacts on energy process (Söderholm, 2012). Bottom-up models are capable of addressing partial equilibrium costs while disregarding economy-wide/general equilibrium costs as well as non-market costs/benefits. Therefore, they normally generate a too low range of mitigation costs estimates (Söderholm, 2012). In spite of this limitation, bottom-up models are useful as they can capture the efficiency improvements and technological opportunities.

16.2.2.3.2 Top down Models

In contrast to bottom-up models, top-down models mainly **focus on the representation of the entire economy, while they largely simplify the technical aspects of the energy sector.** However, because of limited characterisation of technical aspects of the energy system, technology-related alterations such as technical efficiency improvements cannot be explicitly addressed by these type of models (Sathaye & Shukla, 2013). Capital is typically treated as a homogenous input and as an abstract concept, assumed to have some degree of substitutability between energy input in production without explicit modelling of capital equipment (Cambridge Econometrics, 2019).

The macroeconomic perspective of top-down models allows them to analyse interactions between the energy sector and the rest of the economy such as feedback of the economy on energy prices as well as corresponding impacts of energy prices on the demand. They mostly apply aggregate production functions to mimic economic activities of different contributing sectors of the economy. Furthermore, their assessment of energy-economy interactions is restricted by their simplified and limited representation of the energy system (Sathaye & Shukla, 2013). Top-down models are typically used to assess the macro-economic impacts of energy or climate polices, especially market-based instruments.

Commonly used top-down models are for example GEM-E3 (see Appendix for a description), as well as MACRO[176], EPPA (Paltsev, 2005), GTEM (Pant et al. 2002) and WorldScan (Lejour et al. 2006).

Top-down models can further be divided into:

- Computable General Equilibrium Models (CGE)
- Input-Output-Models (I/O-models)
- Macro-econometric models

Computable General Equilibrium Models (CGE)

Computable general equilibrium (CGE) models include all interacting sectors and markets of the economy. They are simulation models that combine economic theory with reported economic data, numerically solved to achieve equilibria across different interacting sectors. The economic data is fed into various model equations, representing the general structure of the economy, simulating the behavior and the interactions between different representative agents such as households, firms and the government. Aggregated CES (constant elasticity of substitution) production functions are applied to simulate the production output from different economic sectors (Chief Economist Directorate, Scottish Government, 2016). Thus, **CGE models consider the linkages between different sectors of the economy** and can assess both the direct economic impacts of various energy and climate policies on individual sectors of the economy such as firms and households as well as impacts of economy-wide policy instruments such as prices on carbon or imposing an emissions trading system (Wing, 2011). One of the leading models is the GEM-E3, which has been applied for rather detailed country-level analysis within the European Union (European Commission, 2018b). Another example is the MS-MRT model, which is a global CGE model (UNFCCC, 2021). This model is particularly relevant for analysing global, socio-economic impacts of climate change mitigation policies and has been applied, for instance, to analyse the impacts of the Kyoto Protocol.

There exist significant **methodological differences among individual CGE models.** The major categories can be identified as *static* and *dynamic* CGE models (Babatunde et al., 2017). Static models provide useful insights into the ultimate losers and gainers from economic shocks though without capturing impacts related of the transition. In dynamic CGE models on the other hand, the capital stock available at a specific year is affected by investments in the previous periods. Dynamic dimensions are incorporated into CGE models through two major approaches: the recursive dynamic model and the completely dynamic model. The recursive dynamic models obtain solutions for each one of many successive years and the equilibrium solution for year *t* obtained is used as baseline year for consecutive year *t+1* without any consideration for intertemporal aspects of decision making of the economic agents. Hence, the economic agents are implicitly faced with myopic or adaptive expectations. On the other hand, complete dynamic CGE models consider forward-looking economic agents with perfect foresight. In this case, economic decisions in period *t* affect parameters in consecutive periods, which, however, rely on the expected values of these parameters. Therefore, a dynamic process is interrelated and the solution has to be sought and solved forward or addressed simultaneously. As a result, dynamic CGE models become very complex and less consideration has been placed on its regional and sectoral details. As the statics type CGE models are not particularly suitable to provide long-term

[176] The MACRO model is a one-sector neoclassical growth model, which is used as a module of the major share of IAM models (e.g. REMIND, MESSAGE-IAM, WITCH) as well as hybrid models (e.g. MARKAL-MACRO, TIMES-MACRO).

assessments of climate change policies, dynamic CGEs are more relevant for assessing long-term mitigation pathways.

CGE models thus provide a consistent framework to analyse direct implications as well as indirect and economy-wide impacts of various energy and climate policies. An important advantage of CGE models is that they model the behavior and interactions between different sectors, representative agents and markets of the economy in an economic-theoretically consistent manner. They trace the circular economic flows within a closed economy, assessing the impacts on key economic variables, including income and expenditure flows. CGE models are capable of analysing both the global welfare effects of imposed policies as well as direct effects of a policy measure on the welfare of individual economic agents. They assess the distributional impacts of policies affected by interactions between different markets (Chief Economist Directorate, Scottish Government, 2016; Wing, 2011).

For instance, when quantity-based policy instruments such as GHG emissions constraint (i.e., an emissions cap) is introduced into these models, the model's solution provides a shadow value linked to this constraint, which can be interpreted as the global price of carbon permits if a permit trading system would exist. In addition to estimating the shadow price of carbon, these models are capable of evaluating macroeconomic costs of climate policies by computing the welfare losses in the policy case compared to the no-policy "business-as-usual" scenario.

While CGE models allow to account for important linkages within the economy, they typically use simplified assumptions to represent mitigation technologies and measures. Moreover, important input parameters (such as factor substitution elasticities and parameters related to energy efficiency and technological change) are mainly derived from historical data. It has been argued that estimating such long-term price responses based on historical data underestimates the economy's flexibility, for instance, in terms of fuel choices and substitutional effects. Therefore, it has been stressed that the CGE approach has an inherent static nature as it assumes that responsiveness to price changes will be the same in the future as in the past, in spite of technological innovation and evolving policy environment (Söderholm, 2012).

Neoclassical growth models

These models are based on modern growth theory. The **utility function is defined as a function of present and future consumption representing household welfare.** They are **not disaggregated into distinct economy sectors but assume an aggregate economy-wide production function.** Neoclassical growth models are similar to dynamic CGE models by focusing on the development of the economy over time. However, growth models do not convey a disaggregated, agent-based representation of individual sectors of the economy in contrast to CGE models. They typically use an aggregate, economy-wide production function with capital, labor and emission-intensive energy services as input factors.

Input-Output-Models (I/O-Models)

I/O models are based on so-called Input-Output tables, which reflect the interrelations between different sectors within the economy. By this, the processes of how which inputs contribute to which outputs in other sectors is reflected. Adjustments are made through changes in quantities rather than price adjustments. As Input-Output-Models mainly reflect a snapshot of interrelations between different sectors within the economy, they are better suited for short- to medium-run analysis, and thus are not the focus of the remaining analysis.

Macro-econometric models

These models **assume that every industry exists in an imperfect competition market**. So, in contrast to the CGE approach, they do not calculate an equilibrium solution. They include demand-driven models, employing econometric techniques to historical data on consumption prices, incomes, and factor costs to model the final demand for goods and services, and the supply from main sectors such as the energy sector (Söderholm, 2012). They can be used to simulate change and/or employed as components in CGE models. Being based on historical trends, macro-econometric models can better reflect short-term adjustment costs in response to climate policy changes rather than long-term implications. Macro-econometric models such as E3ME (Cambridge Econometrics, 2019) argue that their model setup allows to relax some contentious assumptions typically made in CGE models such as perfect knowledge and agents optimizing decisions. Mercure et al. (2019) emphasize that models they label as "non-equilibrium models" have a better representation of innovation and technological change compared to model types typically assuming markets to be in equilibrium such as CGE models and Optimal Growth models, with differing assumptions on financial markets playing an important role (Mercure et al., 2019). Moreover, they have a stronger empirical basis validating model parameters on longer time series reflecting historical relationships instead of (one-year) snapshots (Cambridge Econometrics, 2019).

General strengths and weaknesses of top-down models

In summary, **top-down models typically have a simplified representation of the energy system and available mitigation technologies**. Therefore, they cannot integrate technological innovations (potential costs reductions, efficiency improvements) with the necessary level of detail (e.g. with regard to the number of time slices modelled). This typically limits the applicability of such models in addressing the technology-related questions such as the least cost technology mix to achieve a certain mitigation target.[177]

It is also frequently stressed that the CGE approaches tend to be static in assuming that responsiveness to price changes will be the same in the future as in the past, in spite of technological innovation, evolving values and policy measures. Top-down models thus typically tend to provide a pessimistic range of mitigation costs, since a detailed technological foundation of the mitigation options is often missing. However, as mentioned above, CGE models are particularly relevant when evaluating the economic impacts (general equilibrium costs) of economy-wide policy instruments. If explicitly modelled, this can include non-market costs. For instance, Vrontisi et al. (2016) assesses the macroeconomic and sectoral impacts, both direct and indirect economic impacts, of the European air quality policies[178] of the ''Clean Air Policy Package'' proposed by the European Commission in 2013 applying a CGE model. Generally, CGEs serve to analyse general equilibrium costs.

16.2.2.3.3 Integrating different modelling perspectives

Modelling approaches have also combined the top-down and the bottom-up modelling perspective, typically called **hybrid models**. The categorization between hybrid, top down and bottom-up models is however not clear cut; Many models integrate information from the other perspective while one perspective may still dominate in the model.

Hybrid models **combine the technological explicitness of bottom-up models with the economic comprehensiveness of top-down models**. Hybrid models benefit from linking a bottom-up energy system module with detailed technology representation to a macroeconomy module to endogenously model the interactions between the energy sector and economy. Therefore, hybrid models distinguish between various energy technologies and changes in their

[177] E.g. for assessing the system stability for electricity generation or the needs for storage technologies (batteries) a very high temporal resolution (e.g. hourly) is needed which is typically not represented in top down models.

[178] Focus of this study is the ''Clean Air Policy Package'' proposed by the European Commission in 2013 analysed by applying the CGE model GEM-E3.

relative prices compared to typical top-down models, which typically use aggregate production functions. However, in hybrid modelling, both the bottom-up and top-down aspects are mostly simplified for computational purposes.

One distinguishing factor is the one-way “soft” or two-way “hard” link.

- **Soft-linking:** The soft-link leaves the two models separate and energy supply functions are integrated into the macroeconomy (top-down part) module that are derived from the optimal solution of the energy system module (bottom-up part). The energy supply functions relate the price of energy computed with the energy system module to the quantity of energy computed with the macroeconomy module. An iterative process exchanges price-quantity information between the models. A well-known example of soft linking is the TIMES-MACRO, which integrates a bottom-up energy system model with a multi-sector economic growth model via soft-linking.
- **Hard-linking:** The hard-link approach integrates the techno-economics of the energy system module completely into the macroeconomy module and solves one highly complex optimisation problem. A well-known example of hard linking is the MARKAL-MACRO model.

Well-known hybrid models are for example PRIMES, (see Appendix for a description), as well as MARKAL-MACRO (Loulou et al. 2004), and TIMES-MACRO (Kypreos and Lehtila 2014). However, from the general idea of linking different perspectives most models commonly applied to assess low-carbon long-term transformation pathways can be considered hybrid models.

Another common term used for models that integrate various perspectives or ‘spheres’ from different disciplines in one model suite is **Integrated Assessment Models (IAMs)**.[179] Some Integrated Assessment Models also describe themselves as hybrid models in their model documentation. The term Integrated Assessment Models is not clear cut and moreover used to label a very heterogenous group of models with very different objectives. For the mitigation cost perspective, so-called Cost-Effectiveness Integrated Assessment Models (CE-IAMs) are most relevant for assessing long-term decarbonisation pathways and quantifying the regional and global costs of stabilizing atmospheric GHGs to achieve proposed climate targets. As this requires the use of complex models that combine social, economic, technological, and environmental aspects, these models aim at bringing different spheres together by model coupling (see also Section 10). CE-IAMs are particularly developed to address the question of what the global least cost mitigation trajectory is, given a certain climate target (e.g. temperature target, CO_2 concentration level, etc.), concerning three particular dimensions of flexibility:

- When: Time path (when to take mitigation actions?)
- Where: Regional distribution effects (where to take mitigation actions?)
- How: Which sectors, which technologies, which GHGs?

[179] The term “Integrated Assessment Model” is not clear cut in the literature and the fact that both, models focusing on assessing damage costs and those assessing mitigation costs are referred to IAMs can be confusing (see Box 3). One important differentiation of IAMs for mitigation cost analysis is whether the IAM takes a Cost-Benefits-Analysis perspective (CB-IAMs), i.e. accounts for climate damages or a Cost-Effectiveness-perspective (CE-IAMs), i.e. assumes a pre-defined climate policy target as explained in Section 16.2.2.1 (’decision support tools). While CB-IAMs are discussed in Chapter 10, this chapter mainly focuses on CE-IAMs. Some IAMs like WITCH have the option to include a damage cost function, however can also be run in the cost-effective mode, i.e. ‘turning off’ the damage cost function (see also next footnote).

CE-IAMs have played an important role in assessing long-term transformation pathways in the literature and especially in the more recent IPCC Assessment reports and in multiple model inter-comparison projects. Well-known CE-IAMs are for example WITCH[180], REMIND-MAGPIE and MESSAGE-GLOBIOM.[181] Find an introduction to selected CE-IAMs brief description of selected models that have been regularly involved in recent multi-model comparison studies to assess long-term mitigation pathways and resulting costs in the Appendix.

The evolution of CE-IAM models has particularly focused on the refinement of their energy and land use systems. Having an explicit representation of different sources of energy, greenhouse gases and technologies, the focus of these tools has been to identify the least-cost future emission trajectories and long-term energy system transformation pathways to achieve the proposed climate stabilization targets.[182] Given the great complexity of modelling energy and climate systems (see also Section 17.4.11), most CE-IAMs have relatively simple economic modules, mostly applying the neoclassical Ramsey-type growth theory based on the intertemporal optimisation of consumption.

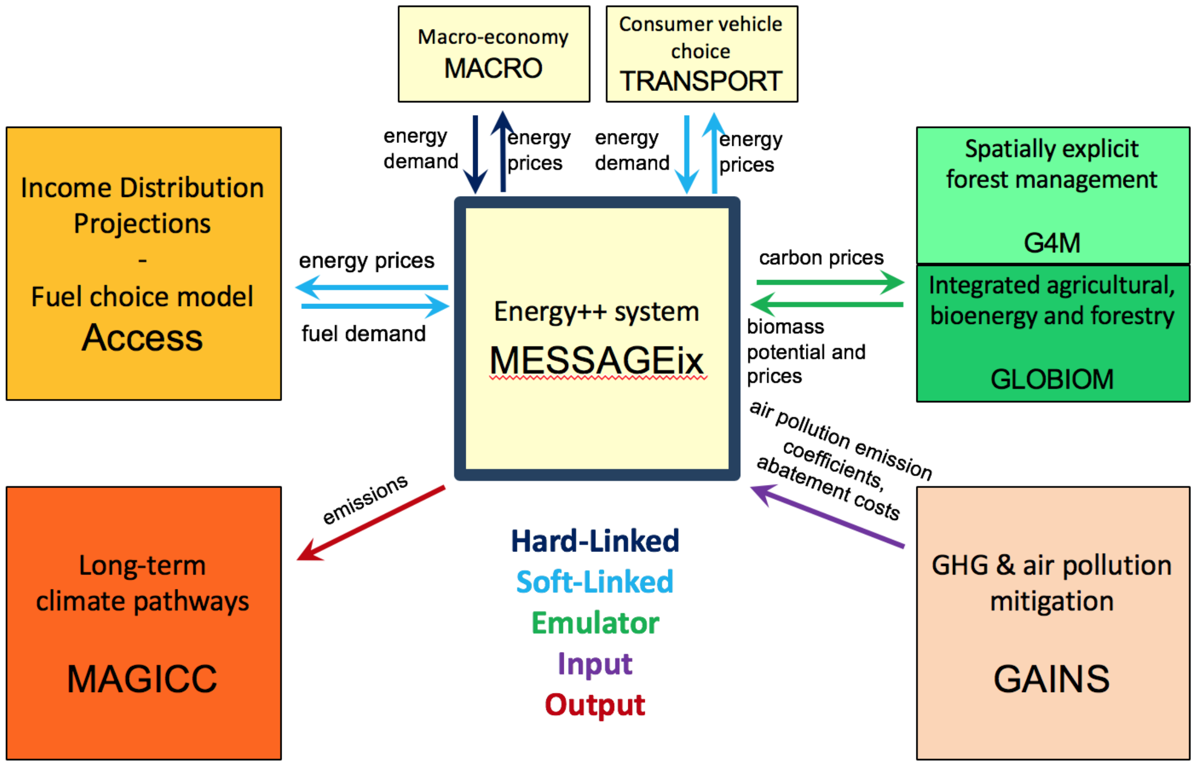
CE-IAMs are generally not a single model but a combination of different models. Most CE-IAMs represent features of both top–down and bottom–up modelling, though they can have a stronger focus on 'bottom-up' or 'top down' perspective. As described for hybrid models, the sub-models in CE-IAMs can either be coupled by soft-linking (information from one model is feed into another model without feedback loops, so-called 'one way' exchange of information) or by hard-linking (two-way exchange of information between models allowing for feedback in both directions) (see explanation for coupling in hybrid models above). Figure 53 gives an example of the coupling of different model-suite-components using the case of the IAM MESSAGE.

[180] Despite the option to include a damage cost function, WITCH is typically run in the cost-effective mode, i.e. 'turning off' the damage cost function.

[181] As the number of existing models is large, this report does not intend to claim a comprehensive coverage of all existing models.

[182] Partly also taking other Sustainable Development Goals (SDGs) into account.

Figure 53: Example of a CE-IAM-model suite for the case of MESSAGE



Note that this represents an overview of the different models that can be linked in MESSAGE, not all versions on the IAM MESSAGE contain all model parts depicted here. All models can also be run on their own with a certain number of exogenous assumptions.
Emulator: A hypercube of precomputed scenarios is developed along key dimensions of interaction between two models. The "driver" model then samples the emulated model hypercube in order to estimate first-order effects of the emulated model. This approach is generally taken when full endogenous coupling (i.e., hard-linking) is either prohibitively computationally intensive or otherwise sufficiently difficult to execute.
Source: Gidden, M. et al. *MESSAGEix: Cutting Edge Research and Challenges*. CNRS Summer School Presentation (2018).

While there is a group of models that is regularly labelled CE-IAM, there are also other models or model versions assessing similar research questions for which the label CE-IAM is not used. Given the very diverse nature of CE-IAMs, the label 'IAM' seems more strongly related to whether a model has participated in a certain modelling community – e.g. as part of model inter-comparisons – than whether a model fulfils strict technical criteria or exhibits specific characteristics.

Given that the different terms used in the literature such as IAMs are not clear cut and often confusing, and that other models typically not labelled IAMs are also of relevance, this study refers to models focusing on assessing mitigation costs (in order to achieve a specific mitigation target) using a more general term **mitigation cost models** (or MC-models).

MC-models can differ greatly with regard to the modules they cover, the level of detail in which various aspects of the system are represented and how various components interact with each other. Some MC-models put special focus on the detail representation of technology aspects of energy system, while others also focus on the land-use sector and macroeconomic feedbacks. Many MC-models include a representation of the energy system and a process-based description of the land system (e.g., Riahi et al. 2017; Doelman et al. 2018; Popp et al. 2017) and efforts to also include air pollutants (e.g. Rao et al. 2017) and water use (e.g. Fricko et al. 2016; Hejazi et al. 2014; Mouratiadou et al. 2016; Zhou, Hanasaki, and Fujimori 2018) have been made. These models therefore allow to analyse the implications of whole-system transformations, including the interaction effects, synergies and trade-offs across sectors (Rogelj, Shindell, et al., 2018). Yet, even complex MC-models typically do not account for all real-world constraints and related costs regarding climate change mitigation action. Some models, such as E3ME, emphasise that – in contrast to most standard models – they allow including real-world features such as inefficient resource utilisation or involuntary unemployment.[183]

There exist large discrepancies between individual models assessing long-term transformation pathways with respect to applied methodologies and assumptions. While some models deal with maximizing welfare as their objective function, others focus on energy system only by minimizing total energy system costs or alternatively soft link the energy system module with the macro module (Bowen et al. 2014; Bauer et al. 2008). Some models use an **intertemporal optimisation** method and assume perfect foresight. Others are **recursive dynamic models**, solved for each time step without agents having full expectations about future circumstances (for more details see Section 17.4.6). Also, there is significant variation across models with respect to their spatial resolution, time horizon, representation of economy, representation of energy system and its technical disaggregation, description of agriculture and land use, foresight as well as degree of integration of model components.

In the Appendix, we provide a brief introduction into selected models that are regularly part of model inter-comparison projects assessing long-term transformation pathways. In Sections 17.4 we further elaborate on the existing heterogeneity in model-specific assumptions and methodologies, further differentiating and classifying those models across several key dimensions.

General strengths and weaknesses of MC-models integrating perspectives

Hybrid models aim to bridge the typical shortcomings of classical top-down and bottom-up approaches through multiple model linking and integration (Holz et al., 2016; Rivers & Jaccard, 2005). So, the main advantage of hybrid models compared to traditional bottom-up or top-down models is that they simultaneously take into account the technological aspects of the energy system in addition to economic impacts. However, in hybrid models both the bottom-up and top-down aspects are typically somewhat simplified for computational purposes. No comprehensive method can cover all information on economic, technological and social perspectives. Many CE-IAMs for example reduce complexity by having a coarser regional and temporal disaggregation (see Section 17.4). Other models reduce the time horizon they look at.

16.2.2.3.4 Comparison of main strengths and weaknesses of different modelling perspectives

Table 22 provides on overview of the main strengths and weaknesses of typical bottom-up, top-down and hybrid models.

The different modelling perspectives also yield important implications for mitigation costs estimates:

Top-Down models, looking at the aggregate costs from a macro-economic perspective, typically assume that the economy is in equilibrium and that markets otherwise work efficiently (if other externalities are not explicitly accounted for). This means that any form of mitigation action entails some net costs to the economy as it deviates from this equilibrium (if the benefits of

[183] See for example the website of E3ME https://www.e3me.com/ (last accesses Nov 22, 2020).

avoided damages from emission reductions are not accounted for as it is the case for Cost-Effectiveness-Analysis)

Bottom-Up models in contrast, taking the micro-perspective, typically assume that there are inefficiencies in the market, i.e. that market forces fail to exploit least cost options without policy intervention. Exploiting these inefficiencies allows for the existence of so-called 'negative cost options', i.e. mitigation actions for which cost savings overcompensate mitigation costs (e. g. savings from energy efficiency measures outweighing the costs).

Table 22: Main Advantages and Disadvantages Top-down, Bottom-up or approaches integrating both perspectives

	Top-down	Bottom-up	Models integrating perspectives
Advantages	• **Reflect interlinkages** within the economy • CGE models are particularly relevant when evaluating the economic impacts of economy-wide policy instruments	• **Detailed** representation of technology options and capital equipment • Provide information on **technologically feasible cost-effective mitigation strategies** • Capture the **efficiency improvements and technological opportunities**	• **Combine the technological explicitness** of bottom-up models **with the economic comprehensiveness** of top-down models • **High comprehensiveness**
Disadvantages	• **Simplified representation** of energy system and available mitigation technologies and capital • Tend to **lack necessary level of detail** of integrating technological innovations (costs reductions, efficiency gains) • CGE approach **tends to be static** in assuming that responsiveness to price changes will be the same in the future as in the past	• Tend to **overlook implementation barriers** such as capital constraints • Tend to **miss interactions** between the economy and energy sector such as the feedback of the economy on energy prices	• Both the bottom-up and top-down aspects are typically **simplified for computational purposes** • CE-IAMs reduce complexity by having a **coarser regional and temporal disaggregation**

These contrasting fundamental differences in assumptions on functioning markets can also be found in different models integrating top-down and bottom-up elements. While many mitigation-models assume perfectly functioning markets and perfect information, IMACLIM is known for allowing for market imperfections and inefficiencies (see Section 17.4.6.4). Also, E3ME allows for market inefficiencies such as spare production capacities and (involuntary) unemployment.

16.2.3 Linking Policy Questions, approaches and cost types

Different approaches are suitable to address different policy questions and to determine different cost types (see Table 23).

Table 23: Linking Policy questions, approaches and cost types

Policy Questions:

	Mitigation target perspective: Assessing the costs of achieving a (long-term) mitigation target	***Technology or measure perspective: Assessing the (current) technology costs and options.***	***Policy instrument perspective: Assessing the costs of related to a certain policy instrument and instrument design.***
Focus	Identifying long-term pathways (and resulting costs) for given target	Prioritization of technologies, sectors	Policy Instrument choice and design
Suitable approaches include	• Cost-Effectiveness- IAMs • Energy economy-models • CGEs	Bottom-up type models, e.g. Financial Accounting, 'measure explicit' MAC-Curves	Very diverse: • empirical impact assessment such as econometric approaches; • top-down models (e.g. CGE models, growth models, Input/Output); • hybrid models • Multi-Attribute-Analysis
Cost types covered	• General or partial equilibrium costs • Non-market costs if explicitly modelled	• Mainly direct financial costs / technology costs	• Depends on focus of assessment, can be narrow or comprehensive • Comprehensive studies may include general equilibrium costs, non-market costs and costs of inefficient policy design
Neglected cost types	• Non-market costs usually not covered • Cost of inefficient policy design • Damage costs	• General equilibrium costs (spill-overs) • Non-market costs usually not covered • Cost of inefficient policy design • Damage costs	• Depends on focus of assessment
Time horizon	long-term	'Static snapshot' (current costs or cost in specific year e.g. 2030), short-term to medium-term	Can be ex-post or ex-ante assessments; Mainly short or medium term
Regional coverage	Usually global assessment with costs estimates differentiated for larger regions world regions (e.g. 'Europe')	Can be global, regional or country-specific, also project specific	Mainly national or regional level

17 Mitigation costs in long-term transformation pathways

17.1 Focus on this chapter

Section 4.1.2 identified mitigation costs associated to long-term mitigation pathways as most relevant to the purpose of this report.

The **focus of the remainder of this chapter** is thus on the mitigation target perspective: Understanding the costs of long-term mitigation pathways for achieving a (pre-defined) mitigation target (Cost-effectiveness perspective) (see Section 16.2.2.1).[184]

The majority of models used in the literature for analysing long-term mitigation pathways and assessing underlying drivers systematically – e.g. in model inter-comparison projects or the IPCC Assessment Reports – are **global mitigation cost models**[185]. These mitigation cost models aim to provide the 'big picture' for the global problem of climate change mitigation and decarbonisation interlinkages between regions. Yet, due to their global coverage these models typically only allow a coarse temporal and spatial disaggregation, e.g. disregarding heterogeneity by aggregating diverse countries into a limited number of model regions and working with larger time steps (e.g. 5 or 10 years).

This coarse disaggregation of global models is often criticized for its limitations in representing real-world complexity and socio-political aspects. **Regional or country-level models** allow representing country characteristics and differences in more detail (e.g. grid connections and differences within regions) and partly include a temporal disaggregation at the level of hourly time slices. This allows an analysis of the implications for energy system stability and storage needs when supply of variable renewable energy sources is growing. This is specifically important for developing decarbonisation strategies on the country or regional level. However, they are less suitable for providing the 'big picture' of global interlinkages of decarbonisation and typically aim at answering more targeted research questions. Moreover, while the scientific community working on global mitigation cost models has made some efforts in defining harmonized input assumptions to allow better comparability between models (e.g. in model inter-comparisons projects), there are less systematic analysis of mitigation cost drivers based on regional or country-level models available, although the landscape of different regional or country level models is also large and very diverse. A noticeable exception are the related journal articles by Capros at al. providing an overview on the main characteristics of seven[186] large-scale EU-focused energy-economy models frequently used in analysis for EU energy and climate policies and defining common scenarios harmonizing model assumptions (Capros et al., 2014a) used as an input for the second study conducting a model intercomparison for these seven models analysing selected drivers across models in a systematic way (Capros et al., 2014b) (see Section 17.6).

There exist large differences between individual modelling frameworks even if classified under the same type of approach. In this chapter, we discuss the heterogeneity in model structures and input assumptions in more depth and how it affects the resulting mitigation cost estimates.

[184] Analyses of long-term mitigation pathways typically build on global models. As the interest of policy makers are understanding the regional (country-specific) mitigation costs, whenever possible we compare mitigation cost estimates for Europe/the EU additional to the global mitigation cost estimates (see section 17.4.5 for a discussion on the regional distribution of mitigation costs).

[185] The literature often refers to such models as so-called "Cost-Effectiveness-Integrated Assessment Models" (CE-IAMs) (also called detailed process IAMs). As the term IAM is also used for other very different types of models (see section 16.2.2.3.3) and not all relevant models would describe themselves as CE-IAMs, we refer to models used for mitigation cost assessment as 'mitigation models'.

[186] PRIMES, GEM-E3, TIMES- PanEu, NEMESIS, WorldScan, Green-X and GAINS.

While the main interest of this chapter are mitigation costs relevant to Germany or Europe, there is also an interest in understanding influencing factors of mitigation costs and differences between model structures which requires building on more systematic analysis such as model intercomparison project results. **Given the more scattered nature of the literature on Europe and Germany, we exploit the large body of literature on systematic assessments of influencing factors for the global models and contrast this with findings on the national or regional models relevant to the EU context whenever possible**. Section 17.6 at the end of this chapter moreover provides summaries for selected studies (scientific articles and policy reports) focusing on the European or German context.

For this report, the **main interest lies in assessing the impact on carbon prices** as these reflect marginal costs (in line with the concept of Social Costs of Carbon in Part 2) and reflect the costs that actors would need to pay for emitting an additional ton of emissions. However, it should be noted that carbon prices are typically considered a flawed metric to assess mitigation costs (Krey et al., 2014; Paltsev & Capros, 2013), as i) marginal costs reflect the cost of the most expensive unit of avoided emissions and thus do not allow drawing conclusions on total or average costs without additional information and ii) carbon prices only reflect true marginal costs under highly idealized assumptions as e.g. they interact with other policies beyond carbon pricing (e.g. energy efficiency standards or environmental taxes) which contribute to mitigation affecting the carbon price level (explained in more detail in Section 17.4.2). While consumers and producers respond to the carbon price, the true measure of policy costs is reflected in their change in behavior as for example reflected in changes in macro-economic consumption (Paltsev & Capros, 2013). Therefore, we additionally discuss estimates on (average) mitigation costs measured by consumption losses or GDP losses or alternative cost metrics.

17.2 Structure of the analysis

The analysis is based on two main pillars:

- ***Literature-based review:*** Insights from the recent literature assessing long-term mitigation pathways, including IPCC assessment reports and model inter-comparison projects or other multi-model studies (see Box 15) are reviewed. Whenever possible, insights from model inter-comparisons for global models are compared with findings from models focusing on the EU or Germany.
- ***Analysis based on the ADVANCE model inter-comparison project and database***: For a more detailed analysis of underlying model characteristics and main assumptions and the resulting implications for mitigation cost rates, we build on the results of the model inter-comparison project "Advanced Model Development and Validation for Improved Analysis of Costs and Impacts of Mitigation Policies" (ADVANCE) and its recently published database. We have chosen the ADVANCE project and database for the following reasons: i) the project had specifically focused on "developing a new generation of advanced Integrated Assessment Models"[187], with certain research articles published under the project looking into underlying methodologies and comparing across models, ii) includes scenarios for limiting global temperature increase to 1.5°C and iii) the database and several research

[187] Website of the ADVANCE project (http://www.fp7-advance.eu/)

articles published under the project also provide scenarios and cost estimates specifically for the European Union, while being comparably recent. In the Appendix, we provide a brief introduction to the ADVANCE project and the participating models. Additionally, data from the IPCC's Special Report on 1.5°C database are used (SR1.5 database release 2.0, (Huppmann et al., 2019)). Note that in parallel to this project, another project[188] commissioned by the German Environment Agency (UBA) has conducted a quantitative analysis of global carbon prices using the SR1.5 database (release 1.1).[189]

Box 15: Model inter-comparison studies

Models often participate in studies that compare the results from different models, e.g. so-called model inter-comparison projects. There exist a wide variety of multi-model comparison studies, applying several models to assess the long-term implications of climate policies (e.g. Kriegler et al. 2013; Kriegler et al. 2014; Kriegler et al. 2015; Luderer et al. 2016).

In the past decade many model inter-comparison studies have been put forward to better understand the main drivers of IAMs results (see also Section 17.4.10 – Cooperation between models). Those studies often aim at harmonizing assumptions across models, by focusing on a variety of model's dimensions such as:

- Energy resources and technological availability (e.g. EMF22, EMF27, EMF33, AMPERE, ROSE),
- GDP, population projections and storylines (ROSE, SSPx),
- Specific regional focus - such as the European Union (e.g. LIMITS, AMPERE) Asia (e.g. AME) and Latina America (CLIMACAP),
- Climate change policies (AMPERE, LIMITS, CD links, ROSE),
- Overall modelling improvements (e.g. ADVANCE).

While harmonizing assumptions across models, those studies shed light on the main determinants of the climate change mitigation cost. In the Appendix, we provide an overview on selected relevant Model Comparison Exercises and their focus questions and areas of harmonization.

[188] Preliminary title: Mark Meyer, Andreas Löschel, Christian Lutz (2021): Carbon price dynamics in ambitious climate mitigation scenarios: A Meta-analysis based on the information content of the IAMC 1.5°C Scenario Explorer. Abschlussbericht zu Arbeitspaket 1 des Vorhabens "Modelle zur Analyse internationaler Wechselwirkungen des EU ETS", FKZ 371842001, Studie im Auftrag des Umweltbundesamtes, Osnabrück, Münster.

[189] Additional to using a different release of the SR1.5 database, the study by Meyer and co-authors decided to exclude individual scenarios from their analyses: Recoding any carbon price pathway as misreported entries that a) had missing global carbon price information for reporting year 2030, or b) had reported year 2030 global carbon prices remaining below 5 US-$/t CO2, leading to and exclusion of 18 simulation result sets from their analysis. Similar to our report, they focus exclusively on ambitious climate protection scenarios ("Below 1.5°C" scenarios, "Low-Overshoot" scenarios, "High-Overshoot" scenarios, "Lower 2°C" scenarios and "Higher 2°C", while we do not include „Higher 2°C" scenarios.

The analysis of influencing factors and their implications for mitigation costs is structured as follows:

- **Overview on the heterogeneity of assumptions and model features**
  - *Heterogeneity in the literature:* What are the main types of assumptions and model features that can be found in the literature? How can they be categorized? How are these linked to other model characteristics?
  - *Heterogeneity in the ADVANCE model inter-comparison project and database (find a short introduction to the ADVANCE project and the database in the Appendix*: How can the models participating in the ADVANCE database be assigned to the identified categories?
- **Implications for mitigation costs:**
  - *Insights on mitigation costs from the literature*
  - *Graphical analysis of carbon prices differentiating groupings of assumptions based on the ADVANCE database*
- **Discussion**
  - *Are the underlying model assumptions realistic? What are the related scientific uncertainties or technical limitations?*
  - *Do the underlying assumptions have a normative character and potential ethical implications?*

17.3 Carbon price ranges in the literature

Table 24: Ranges for global carbon prices from the IPCC Special Report on 1.5°C

Carbon prices converted to EURO2019

Category	1.5°C low overshoot			1.5°C high overshoot			Below 1.5°C*			Lower 2°C		
Year	***2030***	***2050***	***2100***	***2030***	***2050***	***2100***	***2030***	***2050***	***2100***	***2030***	***2050***	**2100**
Median	180	512	2018	76	322	1687	152	274	772	96	324	1458
Mean	289	755	4281	117	496	2805	225	476	2064	145	457	2587
Min	49	108	226	12	97	431	116	210	593	0	65	132
Max	1095	3695	30079	578	3198	11589	408	943	4825	1222	3243	37191

*Note that the category 'Below 1.5C' as assigned in the SR1.5 database only includes a very limited number of pathways (5 pathways of which two do not report carbon price values). Pathways not categorised as Kyoto-GHG|2010 (SAR) = 'in range' have been excluded. Carbon prices converted to EUR2019 using exchange rates from UNCTAD[190] and harmonized CPI from Destatis[191].

Source: own illustration, Climate Analytics based on SR1.5 database (Huppmann et al., 2019).

[190] Conversion from USD2010 to Euro2010 using the exchange rate value 0.75431 (UNCTADSTAT, 2010)

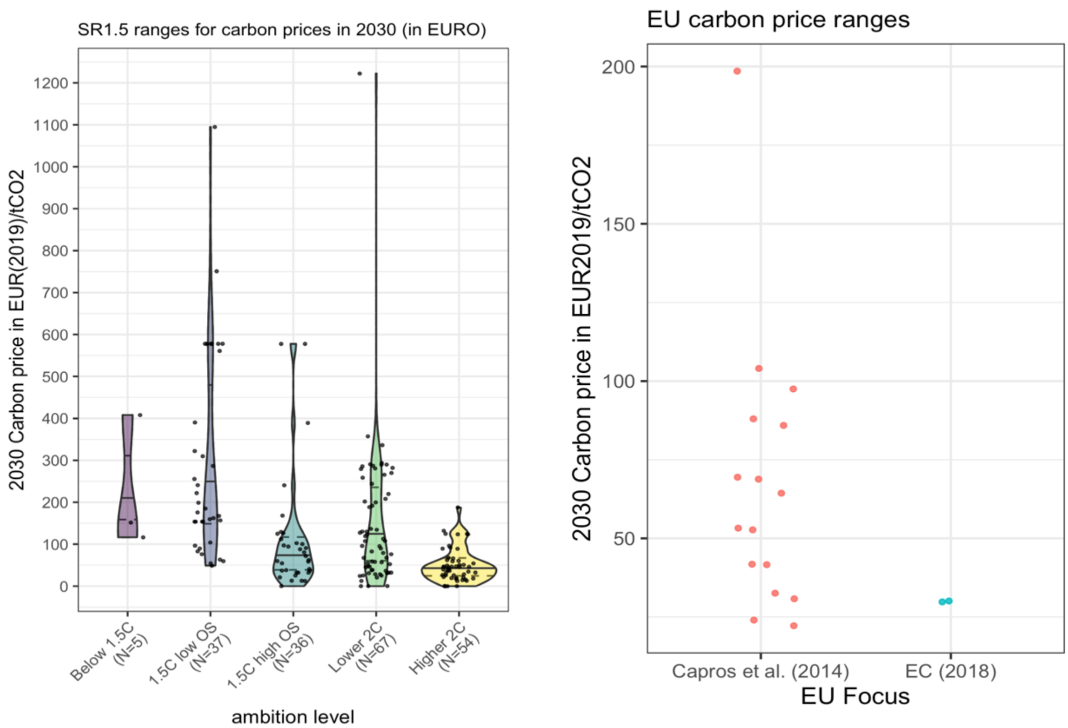
[191] Conversion to 2019 Euro using the Harmonised Consumer Price Index for the respective year (Statistisches Bundesamt (Destatis), 2020)

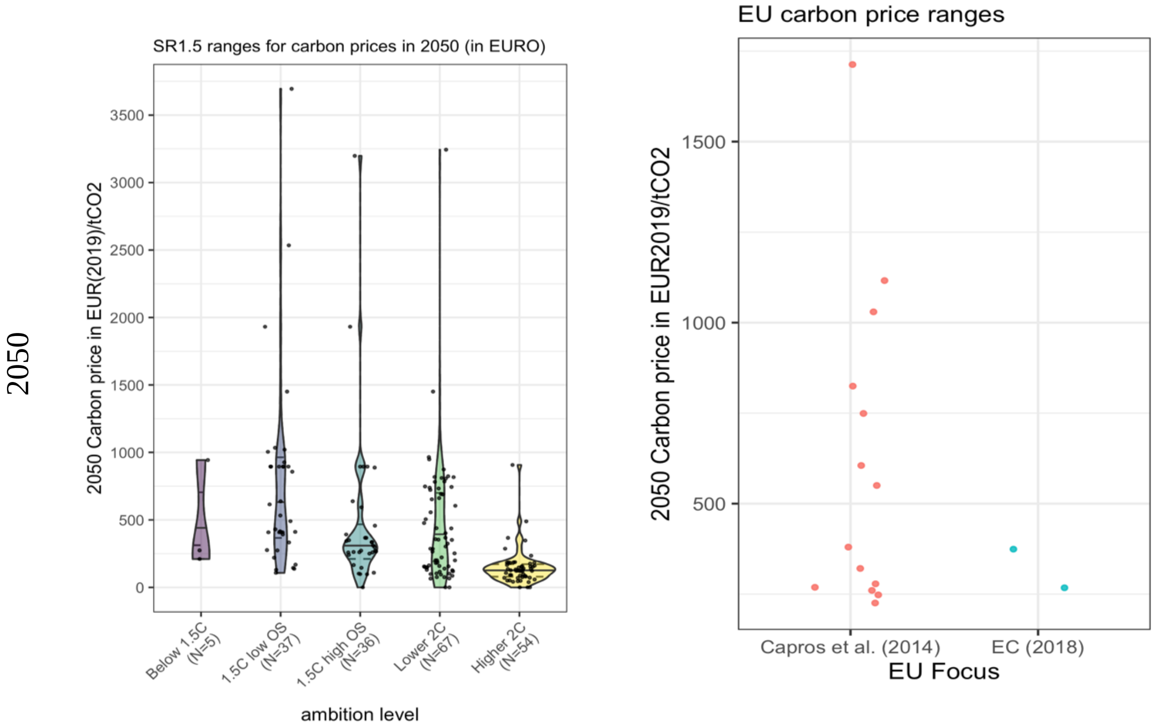
The IPCC Special Report on 1.5°C finds that the (global) carbon price estimates vary substantially between models and scenarios. Table 24 shows the ranges for different pathway categories provided in the SR1.5 database, including median and average carbon prices (converted to Euro 2019).

Figure 54 graphically shows the ranges in global carbon prices for global mitigation cost models from the Special Report 1.5°C (SR1.5) database and compares these to EU-level carbon price estimates of studies focusing on the EU, converted to the same currency and year.

Figure 54: Comparison of carbon price ranges for global models (SR1.5 database) and selected EU-focused studies

	Global carbon price ranges from global models from SR1.5 database	EU carbon price ranges from EU-specific analyses
2030		





SR1.5= IPCC Special Report on 1.5°C. N= number of pathways. OS=Overshoot (temporary overshoot of mitigation target). Carbon prices converted to EUR2019 using exchange rates from UNCTAD[192] and harmonized CPI from Destatis[193]. In the in-depth analysis of the EU Commission (EC 2018), the scenario analysis only starts in the year 2030. Note that in September 2020 a new impact assessment of the European Commission has been published[194]. This was however too late to still be included in this report. The studies by Capros et al. (2014) and the European Commission are discussed in more detail in Section 17.6.1.

Source: own illustration, Climate Analytics based on SR1.5 database (Huppmann et al., 2019), the in-depth analysis of the European Commission (European Commission, 2018a) and the multi-model EU-level study (Capros et al., 2014b).

Differences between pathways become even more obvious when looking into carbon price trajectories over time. Figure 55 illustrates this by filtering out only 'sustainable'[195] pathways from the database of the Special Report on 1.5°C as well as showing carbon prices only until 2050 to improve readability.

[192] Conversion from USD2010 to Euro2010 using the exchange rate value 0.75431 (UNCTADSTAT, 2010)

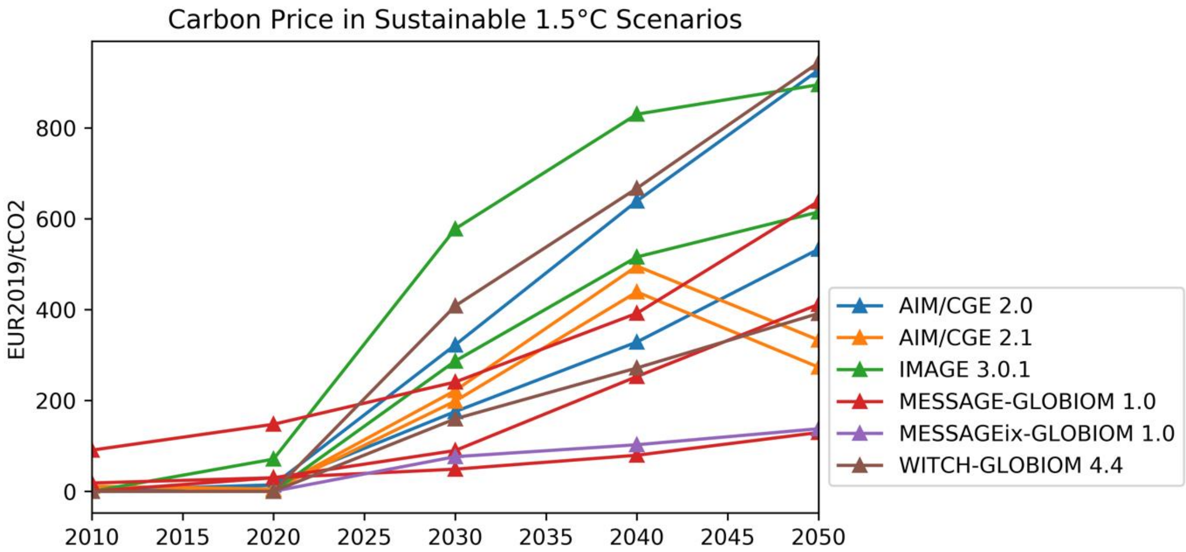
[193] Conversion to 2019 Euro using the Harmonised Consumer Price Index for the respective year (Statistisches Bundesamt (Destatis), 2020)

[194](European Commission, 2020)

[195] The IPCC, based on Fuss et al. (2018), finds limits for a sustainable use of both Carbon Dioxide Removal (CDR) options globally by 2050 to be below 5GtCO_2 p.a. for BECCS and below 3.6GtCO_2 p.a. for sequestration through Afforestation and Reforestation while noting uncertainty in the assessment of sustainable use and economic and technical potential in the latter half of the century. To improve readability, the outlier POLES has been excluded (see Figure 111 in the Appendix for the same figure including POLES).

Figure 55: Carbon price developments over time for filtered pathways from the IPCC SR1.5

Filtering 'sustainable' pathways



Definition of 'sustainable': The IPCC, based on Fuss et al. (2018), finds limits for a sustainable use of both Carbon Dioxide Removal (CDR) options globally by 2050 to be below 5GtCO_2 p.a. for BECCS and below 3.6GtCO_2 p.a. for sequestration through Afforestation and Reforestation while noting uncertainty in the assessment of sustainable use and economic and technical potential in the latter half of the century. Pathways from the SR1.5 database have been filter based on these criteria. To improve readability, the outlier POLES has been excluded (see Figure 111 in the Appendix for the same figure including POLES). Carbon prices in USD2010 have been converted to EUR 2019 using the same conversion factors and sources for these as in Figure 54 (UNCTADSTAT 2010) and (Statistisches Bundesamt (Destatis), 2020)).
Source: own illustration, Climate Analytics based on SR1.5 database (Huppmann et al., 2019).

Throughout the remainder of this chapter, it will be explored in detail how these large differences in carbon price found in the literature estimates can be explained.

17.4 Influencing factors and related uncertainties for mitigation costs in long-term transformation pathways

17.4.1 Overview on main influencing factors affecting mitigation cost estimates

Based on a thorough literature review and analysis of model inter-comparison projects, we identified the following main factors that can have an impact on mitigation cost estimates.

Main influencing factors affecting mitigation cost estimates:

- **Choice of cost metric**
- **Scenario input assumptions**
  - Socio-economic storylines
  - Baseline scenario
  - Policy assumptions: Delay in climate action and fragmented action
  - Level of ambition and overshoot
  - Historical data input and calibration

- **Discounting**
- **Regional distribution of mitigation**
- **General model structure**
  - Equilibrium type and economic system representation
  - Modelling policy details
  - GHG coverage
  - Foresight and solutions mechanism
- **Energy sector and technology assumptions**
  - Energy system detail and assumptions
  - Technological change
- **Pathways characteristics (resulting from differences in underlying assumptions)**
  - Emission pathways
  - Deployment of Negative Emission Technologies (especially BECCS)
  - Demand side mitigation
  - Variable Renewable Energy share
- **Accounting for co-benefits**
- **Modelling Communities**
- **Other influencing factors**

Many of the underlying model characteristics and assumptions are highly interlinked, complicating the analysis of main cost drivers. The main model- and pathway-characteristics listed above as influencing factors for mitigation costs are reviewed and discussed in detail throughout the remainder of this chapter.

17.4.2 Choice of mitigation cost metric

There is no single ideal cost metric to measure mitigation costs available. This section reviews common cost metrics used in models assessing long-term mitigation pathways with a focus on Cost-Effectiveness- models (i.e. assessing mitigation costs for a pre-defined mitigation target).

While the carbon price reflecting marginal costs is of importance to this report, assessments of mitigation costs for long-term transformation pathways (often referred to as 'policy costs') are typically highlighting other cost metrics that better reflect total or average costs. This section discusses the implications for comparing and interpreting different mitigation cost metrics.

17.4.2.1 Importance of differentiating between total, average and marginal costs

For interpreting and comparing mitigation cost estimates it is important to distinguish, whether estimates refer to

- **Total abatement costs,**
- **Average abatement costs**,
- **Marginal abatement costs** (MAC)

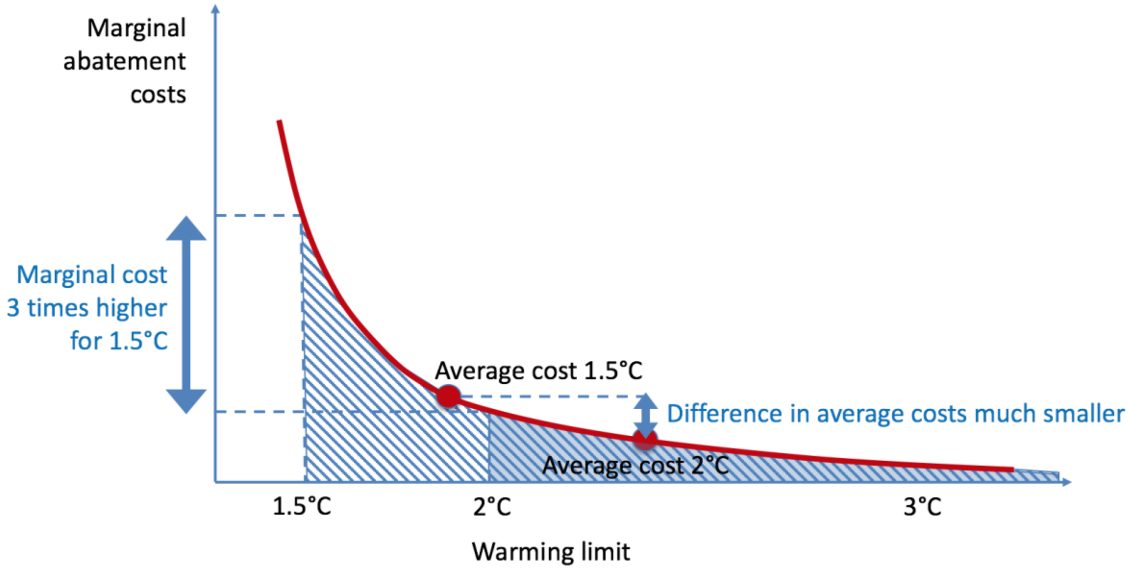
Total costs measure the sum of costs for achieving the envisaged emission reductions compared to a baseline. Typically, total costs refer to the costs over a time span, e.g. the entire time horizon (or lifetime of the policy). However, in the context of our study, we also use the term 'total costs' to refer to the costs for a specific point in time (e.g. consumption loss in the year 2030) to distinguish these from 'average costs per unit of avoided emissions' (see below).

Average costs (per unit of avoided emissions) in our study result from dividing the total costs by the quantity of GHG emissions avoided (measured for example in tons of CO_2e). Average costs are useful when comparing mitigation measures or policies with different levels of emissions reductions. In other studies, average costs can also refer to averaging annual total costs over time (without accounting for avoided emissions).

Marginal abatement costs (MAC) refer to the incremental costs of avoiding an additional unit of emissions. Under an emissions cap with emissions trading, mitigation would in theory take place up to the point where the permit price (emission price) equals the marginal abatement costs. The carbon price is therefore a common metric to reflect marginal costs despite well-known flaws (see Section 17.4.2.2 for a detailed discussion).

Disregarding the distinction between total, average and marginal costs can be very misleading. For instance, for a given scenario, the marginal costs of reducing one additional ton of carbon can be very high while the total and average costs of the respective emission reduction policy may be very low or even negative (Cooper et al., 1996). As marginal costs per definition measure the costs of the most expensive unit of emission reduction, they are per construction higher than average costs. This is illustrated in the figure below for a hypothetical cost curve (see Figure 56). It shows the marginal abatement costs for different temperature limits and compares the marginal and average mitigation cost estimates for achieving the 1.5°C target to the cost estimates of a 2°C target. For this specific illustrative shape of the MAC-Curve, marginal costs for the 1.5°C target are about 3 times as high as for the 2°C target, while the difference in average costs is by far smaller.

Figure 56: Conceptual Illustration comparing marginal costs to total or average costs of different mitigation targets



Source: own illustration, Climate Analytics.

17.4.2.2 Common mitigation cost metrics in models assessing long-run transformation pathways

There is no single ideal metric for reporting mitigation costs available, and different cost metrics are often not directly comparable (Krey et al., 2014). This subchapter provides an overview on common mitigation cost metrics used for assessing long-term mitigation pathways and differences between them.

One frequently used metric which is of specific interest to this study is the **carbon price**[196] (*despite typically referring to all GHGs*). It is typically expressed in USD (or another currency) per ton of CO_2 or CO_2 equivalent (or sometimes per ton of Carbon (tC)). The IPCC's Special Report on 1.5°C emphasises that the price of carbon assessed in mitigation cost models is "fundamentally different from the concepts of optimal carbon price in a cost–benefit analysis, or the social cost of carbon" (Rogelj, Shindell, et al. 2018, page 152). In Cost-Effectiveness-models, the mitigation costs in terms of carbon prices reflect the stringency of the required mitigation efforts at the margin, i.e. the cost of one additional unit of emission reduction (Rogelj, Shindell, et al., 2018). This (explicit[197]) carbon price can be set through a market mechanism trading emission allowances under a cap-and trade system or through an emissions tax that is directly set by the regulating institutions (Paltsev & Capros, 2013). In the modelling world, this means that some models obtain the carbon price as the shadow price of the emissions constraint (simulation of a cap-and-trade mechanism yielding the allowance price endogenously determined in the model), while in other models the carbon price (simulating a tax) is imposed exogenously in a way that the carbon budget (or another pre-defined constraint) is met (Stiglitz et al., 2017).[198] As the

[196] In the literature, the term 'emission price' is also frequently used to reflect that not only carbon emissions are included.

[197] The High Commission on Carbon Pricing differentiates between „explicit carbon pricing" (obtained through a cap-and-trade mechanism or via carbon taxation) and „implicit (notional) carbon pricing" for example via financial instruments that reduce the capital costs for low-carbon technologies (Stiglitz et al., 2017).

[198] In some models, both can be equivalent. For example, in optimization models, the shadow price obtained from a solution with an emissions constraint can be used to produce an identical solution if the price is applied as a tax on the same emissions. This concept is called "duality" in optimisation.

emission price in cost-effectiveness analysis refers to a pre-defined goal, it can be interpreted as 'willingness to pay' for achieving this imposed mitigation (Rogelj, Shindell, et al., 2018).

While the carbon price reflecting marginal abatement costs is of specific interest for this study, the literature on mitigation costs argues that carbon prices are an inadequate measure of policy costs (see e.g. (Krey et al., 2014; Paltsev & Capros, 2013):

- Carbon prices are a measure of *marginal costs,* i.e. the costs of the last and most costly additional unit of emission that is avoided. Carbon prices are an indicator of the 'relative scarcity' of emission allowances compared to the demand for these, not conveying information on the volume of emission reductions and order of magnitude of total cost. The total mitigation costs, in contrast, are the sum costs of all emission reduction that took place at costs *lower* than this emission price. If no information is given on the area below this marginal abatement cost curve (MAC curve), one cannot say how the emission price relates to total or average mitigation costs (Krey et al., 2014).
- If other policies or measures are in place, emission prices can interact with these and do not account for the full marginal costs of emission reductions. For example, if an effective energy efficiency policy is in place, the required carbon price to achieve the same emission reduction target will be lower, as part of the emission reductions are achieved through the other policy. I.e., carbon prices will signal too low marginal costs, as mitigation is partly achieved by the other measures (Krey et al., 2014). However, these interactions can actually lead to higher total policy costs (Paltsev & Capros, 2013). An adequate modelling of market structures and imperfections to be able to provide a more realistic picture of price changes is challenging (Paltsev & Capros, 2013).

Yet, carbon prices can be a relevant cost metric for policy makers and also businesses, as it reflects the additional costs that businesses or public investors would need to factor in for investment decisions, if a price-based policy instrument (carbon tax or emission trading) in line with the mitigation target was implemented.

Due to the strong limitations of carbon prices as mitigation cost metrics, studies assessing mitigation costs typically refer to other cost metrics providing information for total policy costs such as Changes in Consumption, Changes in GDP, Additional Total Energy system costs, Area under the MACC. Below, we provide a short overview of the main concepts and advantages as well as disadvantages for these cost metrics.

- **Carbon price or shadow price:**
  - *General concept*: Marginal abatement cost determined by the imposed mitigation target. As such it measures the price of the last and thus most costly unit of emission that is avoided in the market at the level of the carbon price. Can be interpreted as 'willingness to pay' for a socially imposed mitigation target and as such equals the shadow price of emissions associated with the imposed mitigation target (Rogelj, Shindell, et al., 2018).
  - *Main shortcomings:*
    - Does not provide information how the emission price relates to total or average mitigation costs if no information is given on the area below this marginal abatement cost curve (MAC curve), i.e. the sum costs of all emission reduction that took place at costs lower than this emission price.

    - Emission prices can interact with pre-existing policies, which may signal lower marginal costs as the actual cost would be in the absence of the other policy, as mitigation may partly be achieved by these other measures.
    - Marginal perspective may signal very high mitigation costs though average mitigation costs tend to be much lower.
- *Main advantages:*
    - Reflects the level of carbon pricing that models would suggest to be necessary to achieve a certain mitigation target.
    - Can be a relevant cost metric for policy makers and also businesses, as it reflects the regulatory risks, i.e. the additional costs that businesses or public investors would need to factor in for investment decisions, if a price-based policy instrument (carbon tax or emission trading) was implemented.
- *Unit:* USD (or other currency) per tCO_2 or tCO_2-e
- *Model type:* Typically reported by all CE-IAMs.

► **Change in consumption:**

- *General concept*: Measures changes in the level of (macro-economic) consumption of goods and services by consumers compared to baseline scenario.
- *Main advantage:* Changes in total consumption are generally considered to best approximate the (theoretically ideal) welfare impact by focusing on impacts on a country's population (netting out terms-of trade effects, investments and government expenditures) (Krey et al., 2014).
- *Main shortcoming:* Only approximation of welfare, non-economic costs and benefits are typically not covered.
- *Unit:* Percentage or absolute change (e.g. in USD) compared to baseline scenario for a specific year.
- *Model type:* Requires macro-economic models that capture whole economy (General Equilibrium models)

► **Change in Gross Domestic Product (GDP):**

- *General concept*: Defined as change in the sum of consumption, investment, government spending and net exports (exports minus imports) compared to baseline scenario.
- *Main shortcoming:* GDP loss generally not considered a satisfactory indicator for mitigation costs as it measures impact on output instead of impact on consumers (V. Krey et al. 2014).
- *Main advantage:* Measure of aggregate economic activity that is familiar to general audience
- *Unit:* Frequently measured in % change compared to baseline scenario, sometimes (e.g. in ADVANCE database) also reported in absolute terms (i.e. reduction in consumption compared to baseline scenario in USD or other currency).
- *Model type:* Requires macro-economic models that capture whole economy (General Equilibrium models)

- **Area under the MACC** (Marginal Abatement Cost Curve):
  - *General concept*: The MAC curve depicts the relationship how many tons of emissions can be mitigated at a certain price (Paltsev & Capros, 2013). In the absence of larger economy-wide distortions and under simplifying assumptions, the area under the MAC curve approximates the total economic costs of mitigation compared to a situation without a carbon price.
  - *Main shortcomings:*
    - In the case of large distortions (e.g. pre-existing taxes and terms-of-trade effects), it can lead to substantial underestimation of total policy costs (Paltsev & Capros, 2013).
    - MAC curve is a static approximation to a dynamic abatement process, which limits its applicability.
  - *Main advantages:* Concept to measure total costs in Partial Equilibrium models beyond energy system costs.
  - *Model type:* Can be reported by both, partial equilibrium models as well as whole economy models.
- **Additional Total Energy System Costs**:
  - *General concept*: Costs related to the provision of energy services. Primary energy as production factor to other sectors that cannot be perfectly substituted and thus imposes macro-economic costs. Includes: Capital costs, energy saving costs and energy commodity purchasing costs (fuel and electricity costs including taxes) (Paltsev & Capros, 2013).
  - *Main shortcoming:* Mainly captures costs related to the energy system while neglecting other cost types
  - *Main advantage:* Interpretation of costs is comparably straight forward.
  - *Model type:* Mainly reported by Partial Equilibrium models (Energy models)

Investment costs, e. g. in form of investment needs to transform the energy system, have also been a measure to quantify the costs of climate change mitigation (see e.g. (McCollum et al., 2018)). The analysis of investment costs allows analysing the required changes in the *composition* of the total investment and that the *direction of the investment* i.e. with regard to which technology it flows to, will need to shift substantially.

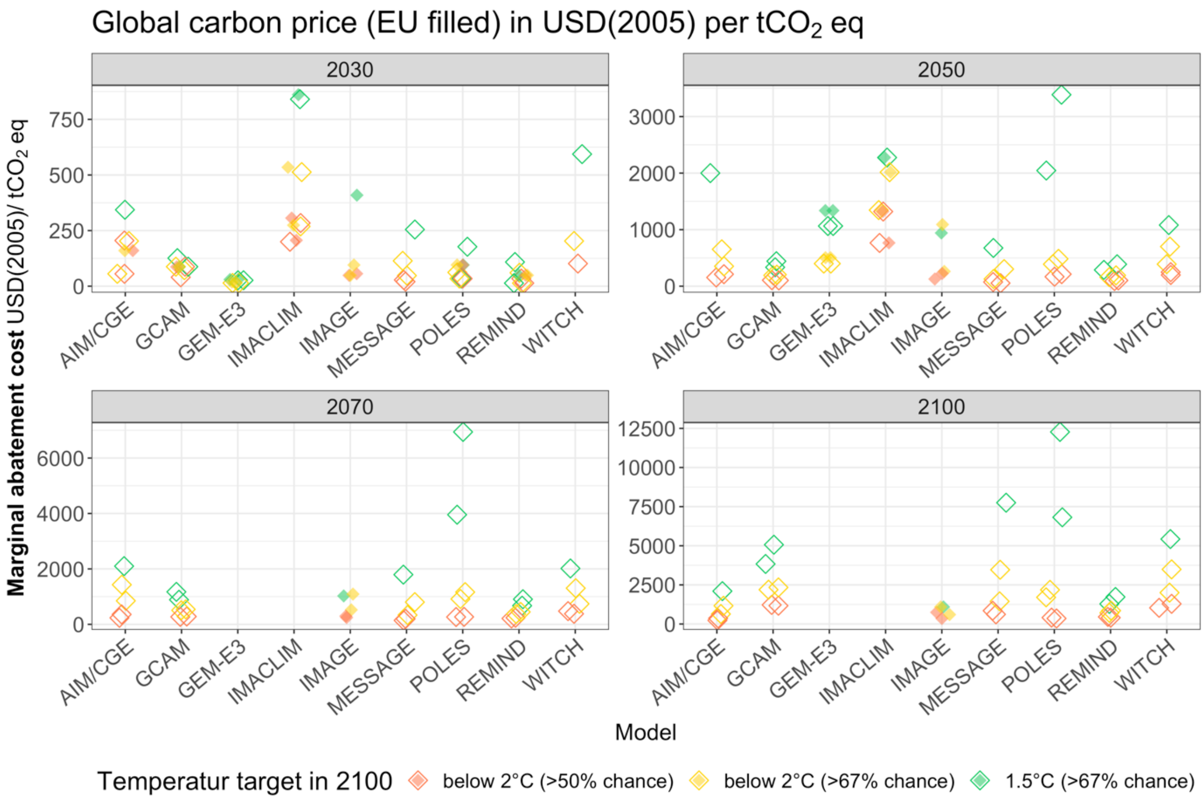
17.4.2.3 Discussion of Implications for mitigation cost levels

Figure 57 shows the carbon prices from the ADVANCE database. Here, the observed spread in carbon price estimates is large, especially in later years, with POLES yielding the highest global carbon price estimate with 12,272 USD_{2005}/tCO_2 (in 2100) (see Figure 57). It should be noted that IMAGE signals comparably low (regional[199]) carbon prices in later years as the modellers have imposed a ceiling value of a maximal carbon tax of 4000USD/tC (1090.91USD/tCO_2) that the carbon price cannot pass. This ceiling value is reached in a large share of the IMAGE-pathways, especially in more ambitious mitigation scenarios, partly by mid-century or earlier.

[199] IMAGE does not report global carbon prices in the ADVANCE database, only regional carbon prices which tend to convert to the same level due to scenario assumptions on timing of global action. Due to the ceiling value assumption, we refrained from calculating an average global carbon price based on regional carbon prices for IMAGE.

Due to this limitation, we either exclude IMAGE comparing global carbon prices or make a note of this limitation for graphs comparing regional carbon prices.

Figure 57: Comparison of Carbon Prices (USD/tCO_2) in ADVANCE database by model and temperature target



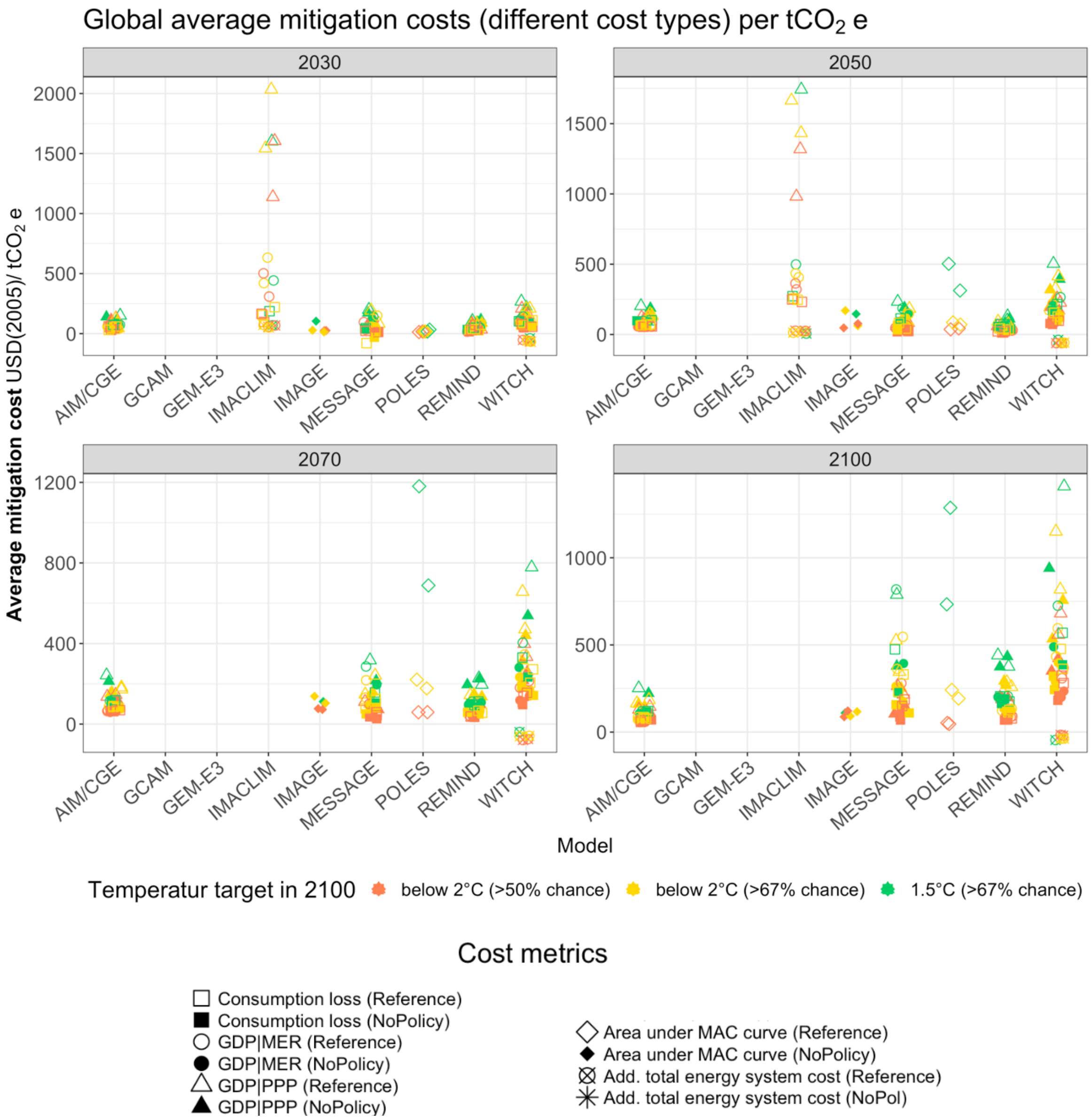
Note: In case the regional carbon price for the EU differed from the global carbon price, the EU carbon prices are indicated with filled squares. MESSAGE = MESSAGE-GLOBIOM. For IMAGE, the modelers impose a cap on the maximum carbon tax value of 1090.91USD/tCO2 (4000USD/tC) which is achieved in most scenarios. Note that IMACLIM and GEM-E3 only report results until 2050.

Source: own illustration, Climate Analytics based on ADVANCE database (IIASA Energy Program, 2019).

The literature on mitigation costs referring to 'policy costs' typically reports **total mitigation costs** in relative changes, e.g. consumption loss in %, which complicates a direct comparison of marginal and total costs. To facilitate a comparison of resulting cost rates, we also plot the average mitigation cost metrics (i.e. total costs per abated unit of CO_2 in a specific year) that we calculated from the ADVANCE database (see Section D.1.5 in Appendix for details) for different mitigation cost metrics available (see Figure 58). Looking at these average mitigation cost estimates shows that for the same model, different mitigation cost metrics can imply very different levels of mitigation costs (for average costs) though all are reported in the same unit (USD_{2005} per tCO_2 for the respective year). For example, IMACLIM reports the largest spread in average mitigation costs, with GDP in PPP[200] losses being substantially higher than GDP losses in Market Exchange rates (MER) and consumption losses. IMACLIM cost rates for 2030 and 2050 – the end of the model's time horizon- are even partly higher than end of century cost rates in other models. Also WITCH, POLES and MESSAGE-GLOBIOM exhibit large spread in average costs by the end of the century.

[200] Purchasing Power Parity (PPP)

Figure 58: Comparison of average mitigation costs (USD/tCO₂) for different costs metrics in ADVANCE by model and temperature target (World)



Average mitigation costs here refer to average costs per abated ton of emissions in the respective year. See Appendix for details how average unit mitigation costs have been calculated. Note that IMACLIM and GEM-E3 only report results until 2050. Changes in GDP, consumption, Areas under the MAC and total energy system costs are calculated compared to different baselines. 'NoPolicy' refers to a baseline without any climate policy. 'Reference' refers a baseline with continuation of climate policies prior to NDC announcement (Cancun pledges).
Source: Calculation based on ADVANCE database (IIASA Energy Program, 2019).

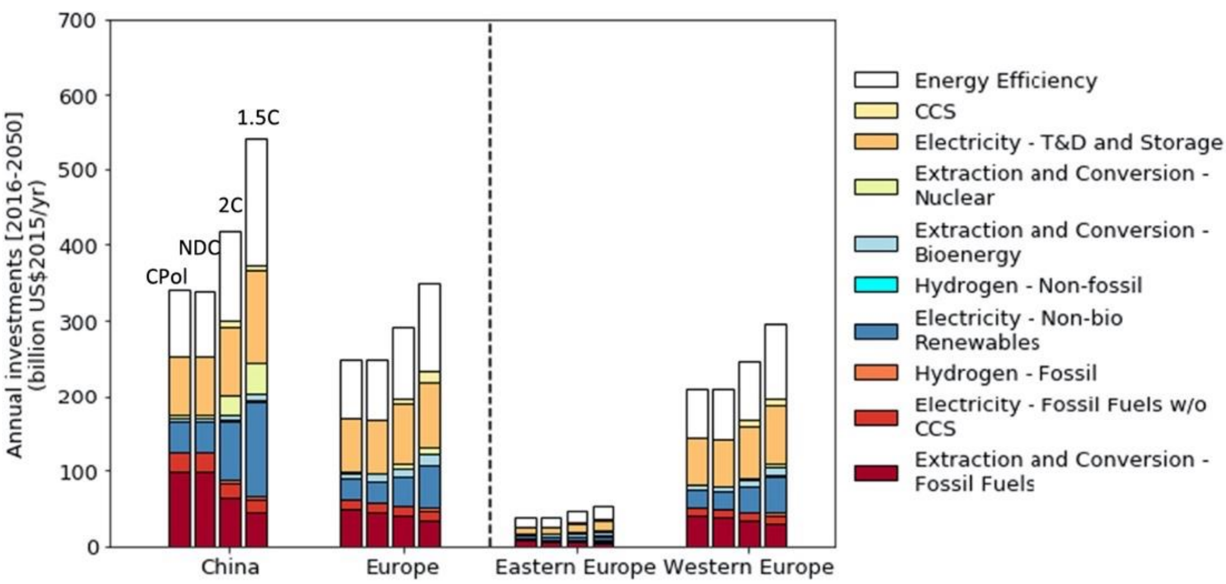
Total or average mitigation costs are generally measured relative to a baseline scenario. In the ADVANCE database scenario setup, both the 'NoPolicy' Scenario and the 'Reference' scenario, can serve as baseline scenarios with different interpretations. The 'NoPolicy' scenario assumes that no climate policies would be in place and the Reference scenario assumes weak climate policy in the form of a continuation of Cancun Pledges (see Section 17.4.3.2). For models reporting data for both scenarios, the difference between the filled and the hollow shape (comparing same shape and same color for same model) signals differences in average mitigation costs levels that result from the choice of a different baseline scenario (see Figure 58). The choice of the baseline scenario matters for the interpretation of the average cost estimates;

as the respective average mitigation costs refer to costs additional to what would have happened in the baseline scenario. Section 17.4.3.2 will go into more detail on the role of the baseline scenario assumptions.

Comparing carbon prices (see Figure 58) with the calculated average mitigation cost metrics (i.e. total costs per abated unit of CO_2) for ADVANCE (see Figure 58), it can be seen that marginal costs tend to be much higher than average costs, especially for more ambitious temperature targets, as marginal costs measure the costs of the last – most expensive – unit of emissions that is avoided.[201]

For **investment costs**, the IPCC SR1.5 finds that annual investment needs in the energy system (based on the average of 7 models) are estimated to be about 2.38 trillion USD_{2010} (1.38 to 3.25) between 2016 and 2035, representing about 2.53% (1.6–4%) of the global GDP in market exchange rates (MER) and 1.7% of the global GDP measured in in purchasing power parity (PPP) (de Coninck et al., 2018). McCollum et al. (2018) provide projections on the investment costs for different ambition levels and investment categories comparing results across six models plus IEA and IRENA estimates. They show that total investment costs for more ambitious scenarios are substantially higher in only two of the 6 models, while the majority of the models projects only comparably minor differences in total mitigation costs. They moreover show that the composition of the total investment matters and that the direction of the investment (e.g. with regard to which technology it flows to) will need to shift substantially in order to achieve Paris agreement compatibility (McCollum et al., 2018). Zhou et al. (2019) estimate the investment costs specifically for Europe and China. Figure 59 shows their estimates broken down by type of investment (Zhou et al., 2019).

Figure 59: Annual average energy investments in China and Europe (2016-2050) by type



Source: Figure 1 from Zhou et al. (2019).[202]

17.4.3 Scenario input assumptions

For the same model, cost estimates will differ depending on the input data and underlying assumptions that are fed into the model. These are examples of the underlying assumptions on economic development, population growth and consumption patterns. Other important

[201] IMACLIM is a strong outlier here, reporting very high average mitigation costs with regard to GDP loss in 2030 and 2050.

[202] Open access article allowing use of content under the terms of the Creative Commons Attribution 3.0 licence.

scenario assumptions are the underlying mitigation target to be achieved and the assumptions on the timing of climate action. Model Intercomparison studies, as well as the modelling community in general, have made some efforts to harmonise these input assumptions to achieve better comparability between models. The implications of the external model input assumptions are discussed in this section.

17.4.3.1 Socio-economic storylines

The analysis of long-term transformation pathways requires a range of assumptions about expected socio-economic developments over time, such as:

- Economic growth (GDP) trends
- Population development (population growth, urbanisation)
- Socio-economic development (e.g. consumption patterns, education)
- Rate of technological development

To bring together these different components and develop plausible scenarios for the different stages the world could be in in the absence of stringent climate policy, researchers from different modelling groups have developed new common scenarios, so-called **narratives or storylines** describing a set of potential futures. A recent example of common narratives to be used to harmonise modelling is the SSPx scenario framework (Rogelj, Popp, et al., 2018), which developed five storylines in relation to challenges to both mitigation and adaptation (see Section 2.4). These SSP narratives are also related to underlying policy assumptions (so-called Shared Policy Assumptions, SPAs), which among other aspects differ with regard to the assumed policy ambitions with regard to near-term ambitions and international cooperation as well as in how far land-use emissions (see Section 17.4.11) are covered by emission pricing (Riahi et al., 2017).

The SSPx database provides country-specific data for both GDP and population in relation to each storyline, which can be used as input for models assessing long-term transformation pathways. Population patterns have been developed in combination with economic projections to ensure consistency in each storyline.

Depending on the type of models employed, GDP can be an endogenous (e.g. WITCH, MESSAGE) or an exogenous variable (e.g. IMAGE, GCAM). In all storylines, GDP growth is assumed to slow down over time with slower growth rates in the second half of the century (about half of those in the first half).

Socio-economic storylines in ADVANCE

In the ADVANCE project, socio-economic input assumptions have been mainly stabilized around SSP2 – middle of the road scenario. However, GDP projections differ as several models treat GDP endogenously. POLES is a strong outlier exhibiting substantially higher values, for both global GDP and global population by the end of the century, compared to all other ADVANCE models (see Figure 113 and Figure 114 in the Appendix).

These common narratives and underlying input assumptions have the advantage of improving comparability of mitigation cost estimates across models. Using the same SSP as an input to different models allows to identify which differences in cost estimates can be attributed to model structure (see Sections 17.4.6 and 17.4.7) for a given stabilization target. The common narratives meanwhile play an important role in the scientific literature as well as for e.g. the upcoming Sixth Assessment Report of the IPCC.

Moreover, it should be noted that the socio-economic storylines also have implications for the choice of techno-economic parameters (see Section 17.4.7) and especially the assumption on lifestyle play an important role for demand side mitigation scenarios (see Section 17.4.8.3).

17.4.3.2 Baseline scenario

Baseline assumptions are strongly related to the socio-economic narratives above. Typically, they reflect expectations on the future development in the absence of (additional) climate policy, representing a 'counterfactual' reference against which to compare mitigation costs in policy scenarios. The underlying assumptions of the baseline such as GDP or population development and consumption patterns (see socio-economic storylines) determine the expected emissions and thus impact the required efforts for achieving a certain mitigation target. As such, the baseline assumptions impact the level of the carbon pricing needed to trigger the required abatement. A meta-analysis by Kuik et al. confirms that higher 'business-as-usual' emission trends makes it more challenging (i.e. more costly) to reach a given mitigation target, estimating that the marginal abatement costs rise by over one percent if baseline emissions increases by 1% (Kuik et al., 2009b). Mitigation cost metrics such as GDP losses, consumption losses or additional energy system costs are measured as changes compared to the respective baseline.

Baseline scenarios may also contain assumptions on pre-existing mitigation policies, such as for example already implemented mitigation policies or RE targets and NDC pledges. In this case, mitigation costs measure the costs of the additional mitigation efforts.

Under simplified assumptions, the carbon price reflects the marginal costs compared to a world without a price on GHG emissions. Yet, also for the carbon price it is important which (pre-existing) policies are represented in the modelled assumptions, as for example energy efficiency policies or other environmental taxes can contribute to emission reductions and thus influence the carbon price level that is necessary to achieve a certain mitigation target (see Section 17.4.2).

In the ADVANCE database, two of the three 'weak policy' scenarios are of main interest[203] for calculating average mitigation costs (see also in the Appendix)

- **'NoPolicy' Scenario**: Counter-factual baseline scenario without any climate policy
- **'Reference' Scenario:** Continuation of climate policy ambition prior to the announcement of the NDCs, accounting for the effects of the Cancun Pledges

17.4.3.3 Policy assumptions: Delay in climate action and fragmented action

A standard assumption in (global) mitigation cost models is that a global uniform carbon price is imposed to achieve the envisaged mitigation level. If no additional constraints are imposed, this assumes that mitigation action is distributed over the time horizon as is found optimal by the model and it assumes that there is a globally coordinated mitigation effort. Also regional or national macro-economic models typically need to make some assumptions on climate policy beyond the respective region. To reflect political feasibility questions, several studies included policy scenarios that diverting from these idealized policy scenario assumptions. Common assessments are:

[203] In the ADVANCE database, not all models report data for all potential baseline scenarios (see Appendix). For our analysis, we therefore assess mitigation compared to both the 'NoPolicy' and the 'Reference' Scenario when reporting average or total mitigation costs whenever possible based on the available data.

- Assessing the impact of a **delay in climate policy action** (e.g. comparing the implementation of a global carbon price in 2030 as compared to 2020).
- Assessing the impact of **fragmented action**, assuming that only certain regions implement ambitious climate polices while others lag behind.

Timing of climate action in the ADVANCE database

The ADVANCE database defines different policy scenarios by combining the temperature targets with assumptions on 'early' versus 'delayed' strengthening of climate action, reflected by the implementation of a global carbon price:

- Early strengthening: Global carbon price in 2020
- Delayed strengthening: Global carbon price in 2030

Secondly, **policies beyond carbon pricing** may be defined as part of the policy scenarios or to reflect assumptions of the underlying socio-economic storylines. These policy assumptions are partly made transparent and partly hidden in the implementation details. Depending on the model, these policies may be mimicked by adjusting techno-economic parameters or by explicitly modelling policies. This may for example relate to policy scenarios assuming larger advancements with regard to energy efficiency (see e.g. EC in-depth analysis or the multi-model study for the EU by (Capros et al., 2014b) both in see Section 17.6). As mentioned in Section 17.4.2 and 17.4.3.2, such assumptions on other climate policies can influence the required carbon price to achieve a certain mitigation target as part of the emission reductions are achieved by measures other than the carbon price. Also policy design matters; (Weyant, 2017) suggest that mitigation costs can be very sensitive with regard to the assumptions about policy implementation specifics, e.g. policy instrument choice and the design of policy instruments. Optimal Growth-models typically abstract from implementation details or instrument design. CGE-models are better suited to analyse policy details (see Section 17.4.6).

Other policy assumptions may relate to end-use sectors as for example assuming different policy scenarios with regard to electrification of transport (Capros et al., 2014b).

17.4.3.4 Level of ambition and overshoot

Another important assumption which is exogenously defined in Cost-Effectiveness Models is the level of ambition to limit climate change. This imposes a constraint on the model to calculate the respective mitigation costs (compared to the above discussed baseline) for the given mitigation ambition.

The **level of ambition can be defined in different metrics** such as i) temperature limits[204] (in °C of mean temperature increase compared to pre- industrial time), ii) atmospheric concentration levels (in ppm), iii) cumulative emissions' limits typically expressed as so-called carbon budgets[205] (in Gt CO_2) and iv) radiative forcing (in W/m_2) e.g. used in RCP Scenarios (see also Section 2.4). Taking the limited understanding of the climate system and the resulting scientific uncertainties into account, one metric can be translated into another metric reflecting

[204] The temperature limiting refers to mean temperature increase above pre-industrial times. Note however, that the underlying metric to measure those temperature increases can differ. In the IPCC's Fifths Assessment Report, the metric Global Mean Surface Temperature was used. For the upcoming Sixth Assessment report, scientists suggest to use a different metric referring to air temperature as science advances. The change in metric and some other methodological improvements lead to differences in current global warming levels of more than 0.1°C comparing the 'old' AR5 metric and the new AR6 metric.

[205] Carbon budgets are frequently defined to refer to CO_2 only. Few studies define GHG emission budgets in CO_2 equivalents.

ambition levels. Several Integrated Assessment Models have a climate module or are linked to a climate model, such as MAGICC or FAIR (see Section 17.4.11) to translate emissions into climate outcomes such as forcing and global mean temperature change. However, the translation of cumulative emissions into temperature increases is not without controversy, with different studies yielding very different results with regard to the allowable carbon budget for very low emission scenarios like 1.5°C temperature limits.[206] Thus, for models that utilise different climate modules, it may be possible for slightly different carbon budgets to be reported even for a common temperature target – with implications for the required mitigation efforts and related costs. In some model intercomparison projects, as done in the ADVANCE database (see Box 16), temperature limits are directly linked with certain 'Carbon Budgets', i.e. defining a limit for the maximum cumulated amount of CO_2[207] that the atmosphere can still absorb before crossing the threshold of the temperature limit.[208]

Box 16: Temperature limits and carbon budgets in ADVANCE

In the ADVANCE database, three different ambition levels defined in terms of temperature limits have been analysed. For these, fixed carbon budgets have been defined for the analysed temperature limits, harmonising the allowed emissions across models. The temperature limits and associated carbon budgets in ADVANCE (cumulative CO_2 from 2016-2100) for the respective temperature limits are[209]:

- Chance of 50% of staying below 2°C ('Med2C'): limit cumulative 2011-2100 CO_2 emissions to 1600 $GtCO_2$ (corresponding to ~1400 $GtCO_2$ from 2016-2100);
- Chance of 67% of staying below 2°C ('WB2C'): limit cumulative 2011-2100 CO_2 emissions to 1000 $GtCO_2$ (corresponding to ~800 GtCO2 from 2016-2100);
- 1.5°C (>67% chance of limiting 2100 warming to 1.5°C): limit cumulative 2011-2100 CO_2 emissions to 400 $GtCO_2$ (corresponding to ~200 GtCO2 from 2016-2100);

Alternatively, policy scenarios in the literature can also relate to specific policy goals, e.g. as defined in strategy documents or referring to pledges made in international negotiations such as the Kyoto protocol or the Paris Agreement's NDCs, e.g. defining a percentage reduction of emissions compared to a certain base year. This is more common in studies focusing on certain regions or countries and the respective political targets.

The emissions or temperature limit in Cost-Effectiveness Analysis is a normative choice for policy making, with the Paris Agreement providing a clear benchmark since 2015. However, there are **many additional related choices with a strong normative character** which leave room for interpretation about what is in line with the Paris Agreement. Together with the net-zero greenhouse gas mitigation goal expressed in Article 4, the temperature goal of "well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels" (Article 2a, UNFCCC 2015) allows for two interpretations (Schleussner et al., 2016, 2019): holding warming below 1.5°C, or allowing for a temporary overshoot above the 1.5°C limit, while holding warming to 'well below 2°C', implying a better

[206] For more information see e.g. this explainer by Carbon Brief (Hausfather, 2018).

[207] Depending on how the carbon budget is defined, it can refer to CO2 only or to CO2 equivalents (CO2e).

[208] Note that the magnitude of the remaining CO_2 budget for 1.5°C is highly uncertain, depending on assumptions on current warming, non-CO_2 emissions and abatement, climate sensitivity and the way the limit is specified (e.g. the probability to stay below the temperature limit.

[209] ADVANCE database website (IIASA Energy Program, 2019)

than likely (66%) chance which was previously associated with the pre-Paris 'below 2°C' goal. The IPCC Special Report on Global Warming of 1.5°C has constrained plausible overshoot pathways to no or low overshoot pathways that are as likely as not to limit warming to 1.5°C (Masson-Delmotte et al., 2018).

These interpretations imply that there are **several choices that can lead to seemingly equal temperature limits to be associated with different ambitions levels**. These are:

- Differences in the **probability** defining the scientific probability of remaining within the temperature limit. Lower probabilities reflect less ambitious mitigation levels for the same temperature limit. Common probabilities used in the scientific literature are 50% and 66% (two thirds probability sometimes also rounded to 67%).
- Whether it is defined as a strict temperature limit or an 'end of century' temperature limit[210] allowing for (temporarily) **overshoot** (OS) of emissions and higher peak warming levels (Clarke et al., 2014). In the IPCC's Special Report for 1.5°C groups pathways into 'high overshoot' and 'low or no overshoot'. Overshoot scenarios usually are closely linked to the (large scale) deployment of negative emission technologies (see Section 17.4.8.2). The Fifth Assessment Report of the IPCC concludes that in overshoot scenarios, the likelihood of exceeding a temperature limit within this century is higher as peak concentration levels are higher. The recent IPCC Special Report on 1.5°C (Masson-Delmotte et al., 2018) explored a large collection of overshoot pathways for 1.5°C, including scenarios leading to a peak warming up to 1.9°C around mid-century that subsequently reach warming of below 1.5°C by 2100. That same report also identified substantially lower risks/damages at 1.5°C warming compared to 2°C. During the "overshoot period" a 1.5°C pathways that reaches 1.9°C would approach damages more typical of 2°C warming than of 1.5°C, some of which may be irreversible. It is therefore important to keep in mind that lower mitigation costs for certain mitigation pathways for the same long-term climate stabilization goal are not necessarily associated with the same climate damages and that the potential implications for damages from climate change resulting from the temporary overshoot are not taken into account in Cost-Effectiveness models.

Overshoot in the ADVANCE database

In the ADVANCE database, almost all stabilization pathways require net negative CO_2 emissions towards the end of the century, some 1.5°C pathways even by mid-century already (see Figure Figure 84 in Section 17.4.8.1).

The maximal ratio of overshoot (cumulated CO_2 compared to carbon budget for 1.5°C) goes up to 3.7 (REMIND, in the 1.5°C Scenario with delayed strengthening), thus temporarily exceeding 200 Gt carbon budget for 1.5°C target almost by a factor of 4 (745Gt CO_2).

Moreover, some pathways miss the carbon budget target in 2100 by over 100 Gt CO_2. 100Gt CO_2 deviation had been deemed an acceptable tolerance as the deviation is equivalent to only about 3 years of current emissions. However, given that the 1.5°C target carbon budget in ADVANCE

[210] Typically, those temperature limits define that the mean global temperature change needs to revert to the target temperature by 2100.

(2016-2100) is only 200Gt CO_2, the tolerated deviation from budget limit amounts to half of the carbon budget for 1.5°C.

17.4.3.5 Historical input data and calibration

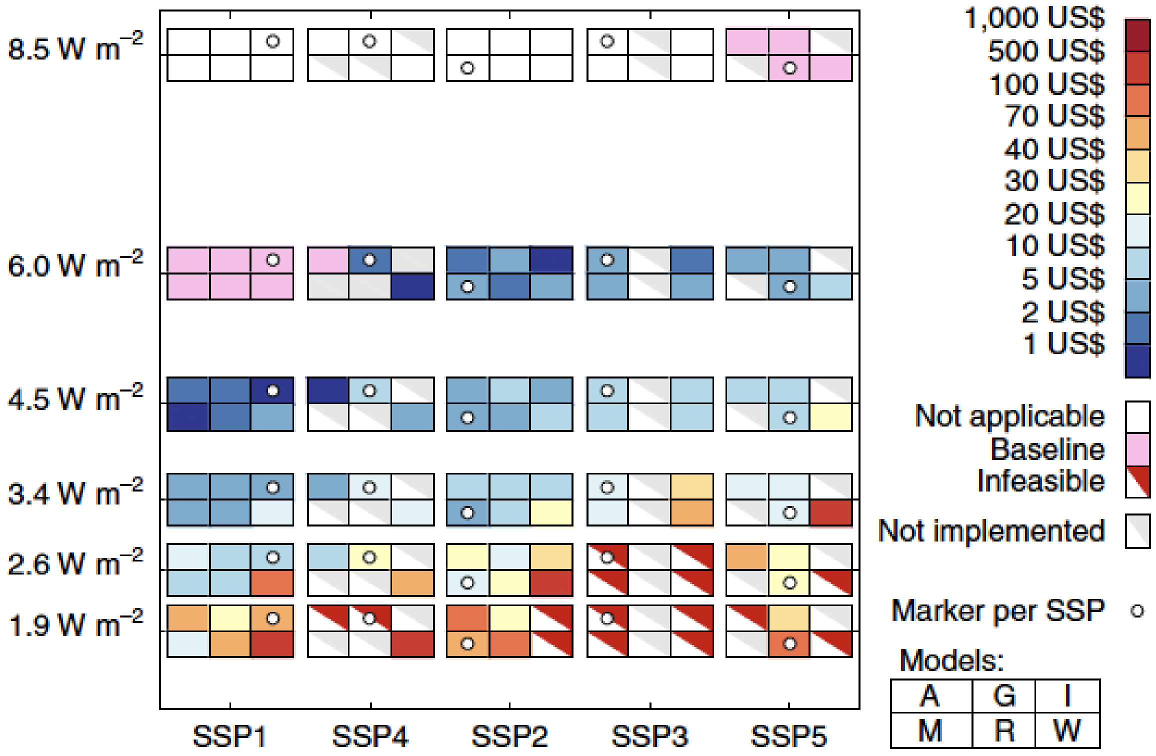
CE-IAMs typically use historical data to calibrate the models. However, the underlying historical data may be outdated as there is typically a certain time lag resulting from i) official data sources publishing historical data for 2017 only in 2019 or later, ii) models requiring time and effort to take newer data into account and iii) a time lag between modeling results are produced until these are finally published (in scientific journals or databases e.g. from model inter-comparison projects like ADVANCE). The ADVANCE project for example started in 2013 and ended in late 2015. However, many of the publications have only been published in 2018 and the scenario database of the ADVANCE project compiling the results from the different project components and publications written under the project was launched in mid-2019. As a consequence, input data on e.g. historical emissions for CO_2 in the ADVANCE database start to diverge for the different scenarios already in 2010 for many models. This can lead to a strong mismatch of modelled (projected) emissions for 2015 and meanwhile observed 'historical' emissions for 2015 or later.

17.4.3.6 Implications for mitigation costs

Both, **ambition level for mitigation** and **socio-economic storylines** can largely affect the mitigation cost estimates. Assuming a high population growth generally leads to higher projected GHG emissions and thus higher mitigation costs to achieve a given stabilization target as more emissions need to be avoided. Similarly, a higher GDP growth (if mainly based on fast development of energy intensive industries fossil fuel-based energy supply) would also lead to high future emissions and higher required efforts to curb emissions to a given target (O'Neill et al., 2014).

Likewise, assumptions about consumption patterns (e.g. assumptions on energy efficiency or dietary changes or more generally a switch to more sustainable lifestyles) and technological change affect how high emissions in the **baseline scenarios** would be projected to be, and thus how large the reduction in emissions would need to be for a given target. For example, assumptions regarding the electrification rates, agricultural yields, technologies for reducing non-CO_2 emissions, behavioral change and lifestyles can lead to significant changes in emissions (van Vuuren et al., 2018). All of these options if combined can significantly reduce the emissions in the baseline scenario and reduce the need to apply (costly) carbon dioxide removal technologies to achieve more ambitious climate stabilization targets [see also Section 17.4.8.2 on negative emission technologies and Section 17.4.8.3 on demand side mitigation].

Figure 60: Variation in carbon prices over SSP and radiative forcing scenarios



Note: Values are shown as average global average carbon prices over the 2020–2100 period discounted to 2010 with a 5% discount rate. Mitigation challenges are assumed to increase from left to right across the SSPs (that is, SSP1, SSP4, SSP2, SSP3, SSP5). Each box represents one model–SSP– radiative forcing target combination. A: AIM/CGE; G: GCAM4; I: IMAGE; M: MESSAGE-GLOBIOM; R: REMIND-MAgPIE; W: WITCH-GLOBIOM. All scenarios with a carbon price greater than 0 (that is, all but the baselines) have been designed to reach one of the radiative forcing targets on the vertical axis. Models for which no baseline data are indicated have baselines that result in an end-of-century radiative forcing between 6.0 and 8.5 W m^{-2}. [Added by authors:] Marker per SSP: for each SSP a marker implementation was selected that represents the characteristics of the respective SSP scenario particularly well. This marker is highlighted with a dot.
Source: Figure 5 from Rogelj, Popp, et al. (2018).[211]

It is recommendable to also compare the mitigation costs for different ambition levels while accounting for differences in baseline scenario narratives. Figure 59 from Rogelj et al. (2018) shows a matrix of carbon prices for different SSP narratives (x axis) and stabilization targets (y axis). It can be seen that less ambitious targets (i.e. with a higher radiative forcing) result in lower mitigation costs, while SSPs that are more pessimistic about how baseline emissions evolve exhibit higher mitigation cost estimates for a given stabilization target. Importantly, the comparison across SSP and stabilization targets illustrates that assumptions about the world's development in the future can have strong implications for the feasibility of actually achieving certain climate targets. For example, the SSPx comparison study (Rogelj et al. 2018) confirms that all model runs characterized by sustainability storylines (e.g. SSP1) were able to successfully achieve the Paris Agreement long-term pathway (RCP 1.9 w/m2). Storylines with moderate challenges for mitigation (e.g. SSP2) often led to increasing carbon prices. Finally, other storylines that are more pessimistic and project high challenges for mitigation were often not even able to produce a feasible solution for the most stringent climate targets, indicating prohibitively high associated mitigation costs (see Figure 59).

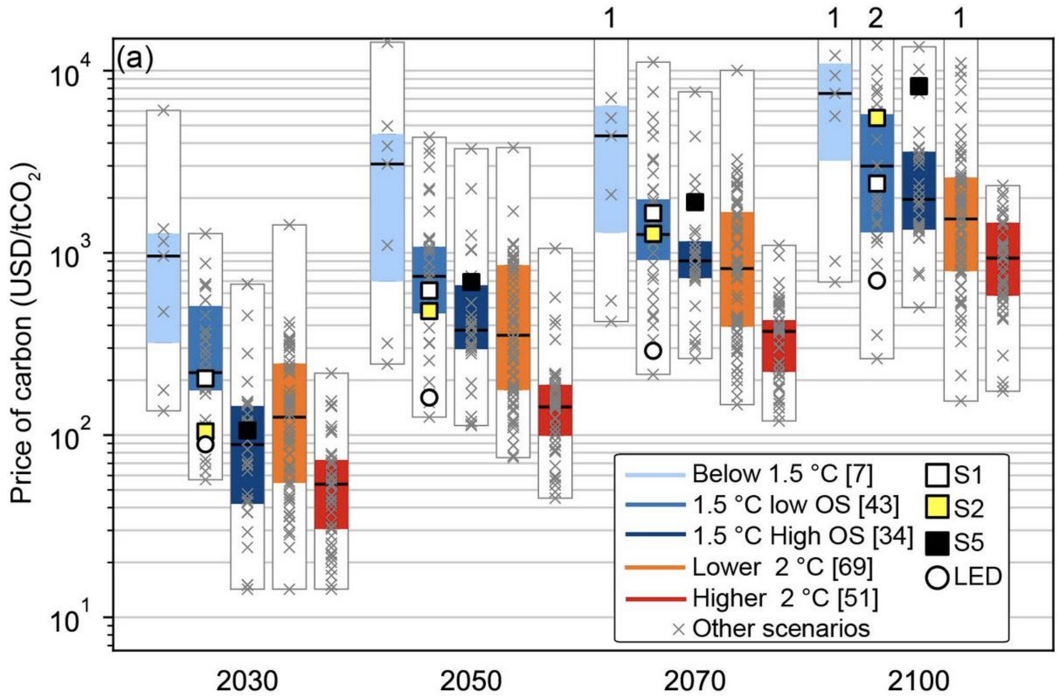
[211] Permission for using the figure has been obtained under the licence number: 5012560701445.

Note that in addition to the stabilization target, further assumptions on technological development, as incorporated in the various SSPs, also affect mitigation cost. For example, under the SSP3 (characterized by fragmentation and lack of technological cooperation across countries) or the SSP5 storylines (fossil fuel development), models were often not able to produce a "feasible" solution for the most stringent climate target (e.g. RCP 1.9 w/m2, which is in line with the Paris-Agreement long term goal). This will be discussed in more depth throughout the next subsection, where the focus is laid on the implications of differences in model specific assumptions, also covering assumptions on technologies among others.

Attempting to quantify the relative contribution of SSP choice with regard to carbon price variation Guivarch and Rogelj find that for the sample of RCP2.6 scenarios from the SSP database, the differences in socio-economic assumptions represented by the SSPs explains only about 10% of the total variation in carbon prices in their sample (Guivarch & Rogelj, 2017). They explain this rather small contribution of the SSP scenario by the fact that scenarios that resulted in infeasibility issues could not be included in the analysis. Quantifying the changes in carbon prices between different SSP scenarios, Guivarch and Rogelj state that, in the analysed scenario set, shifting from SSP2 to SSP1 led to carbon prices in 2050 almost halving for most of the models they analysed, with the minimum being seen for the WITCH model (15% reduction) and the maximum observed for the IMAGE model (almost 80% reduction) (Guivarch & Rogelj, 2017). Shifting from the SSP2 to SSP5 (high mitigation challenges), they found a robust increase of carbon prices in 2050 as expected, ranging from 10% to 70% increase (though it should be noted that only 3 models of the 6 models in their set had looked into SSP5).

The IPCC Special Report on 1.5°C also assesses the implications for carbon pricing, including a differentiation of model results with regard to overshoot (see Figure 61). It shows that more stringent mitigation targets (including restricting the amount of temporal overshoot) typically exhibit higher carbon prices, with a decreasing differential towards the end of the century. The SR1.5 identifies substantially **smaller carbon budgets for more ambitious scenarios as the main driver for differences in carbon prices**, based on studies conducting pair-wise comparison of scenario results (Luderer et al., 2018; McCollum et al., 2018).

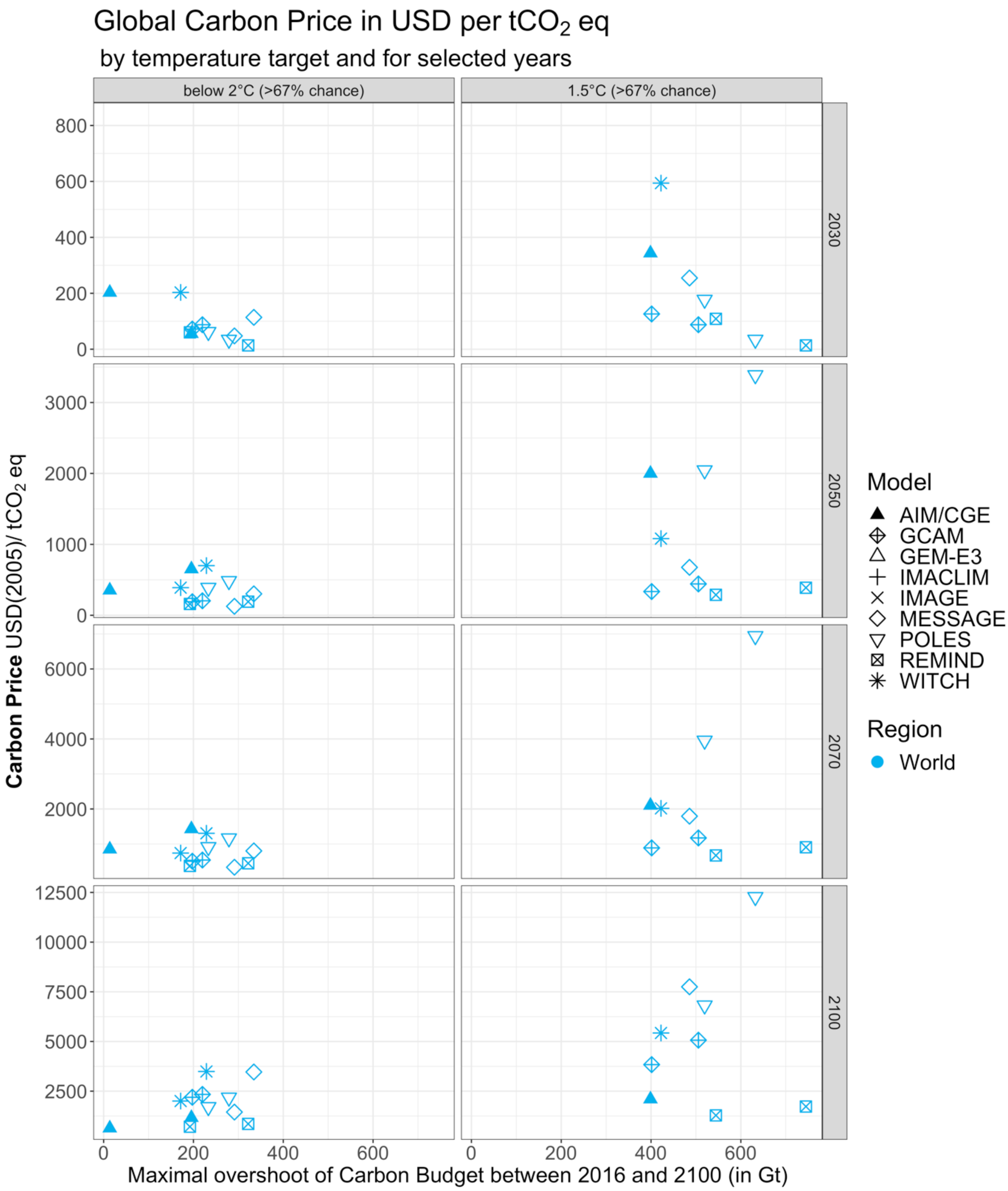
Figure 61: Global Carbon Price ranges by temperature target and overshoot (IPCC SR on 1.5°C)



Note: Undiscounted price of carbon (2030–2100). Median values in floating black line. The number of pathways included in box plots is indicated in the legend. Number of pathways outside the figure range is noted at the top.
[Added by authors:] OS: Overshoot. LED: Low Energy Demand-Scenario. Carbon prices in USD_{2010}.
Source: IPCC SR 1.5, Chapter 2, Figure 2.26 a, on page 153 (Rogelj, Shindell, et al., 2018). Original title: Global price of carbon emissions consistent with mitigation pathways. Original figure also contains a panel b (not shown here) on “Annual compounded net-present-value carbon price from 2030 until 2100”.

Figure 62 shows the carbon prices from the ADVANCE database by carbon budget overshoot. The picture is not very clear. In the 1.5°C, the 2030 carbon price implies that higher overshoot is associated with lower near-term carbon prices (though the carbon price range is large for lower overshoot scenarios here) – as less ambitious near-term action can be compensated later e.g. by applying negative emission technologies. One would expect that this would lead to higher long-term carbon prices in higher overshoot scenarios. In fact, for REMIND and GCAM, this expected tendency can be observed (both for the 1.5°C and the less pronounced also for the 2°C scenarios), however with a relatively minimal differences in carbon price levels between the low and the high overshoot scenario in our sample. In POLES, this pattern is stronger in our sample.

Figure 62: Differences in global carbon prices by overshoot of temperature target in ADVANCE



Note differences in the y-scales to improve readability. MESSAGE=MESSAGE-GLOBIOM. Carbon budget in ADVANCE for below 2°C (>67% chance) = 800GtCO2, for below 1.5°C (67% chance) = 200GtCO2. Note that IMACLIM and GEM-E3 only report results until 2050. Note a potential selection bias for 1.5°C scenario results due to potential infeasibility issues to produce results for very ambitious scenarios. Note that POLES assumes substantially higher population growth (see Appendix Figure 113).

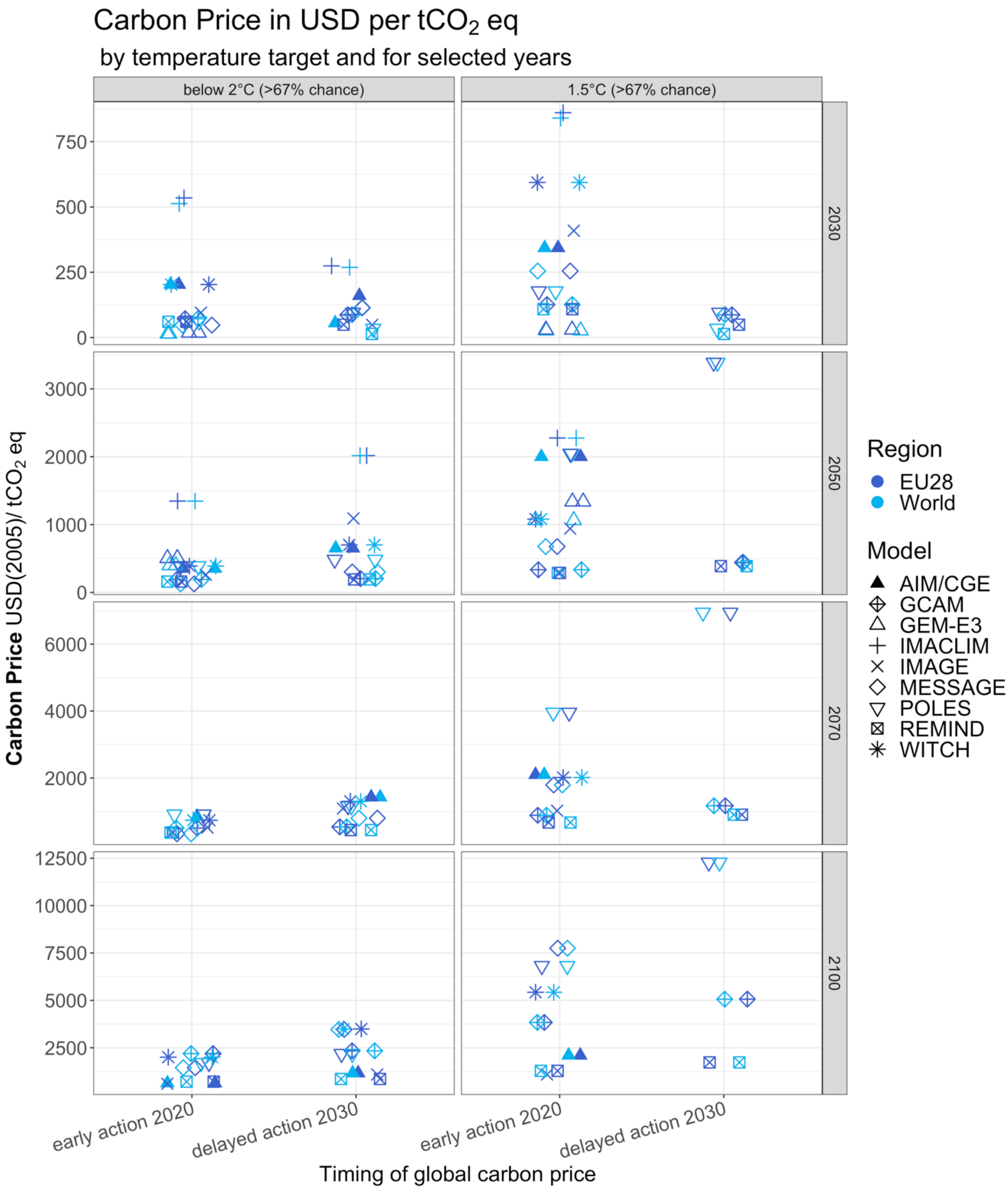
Source: own illustration, Climate Analytics based on ADVANCE database (IIASA Energy Program, 2019).

Several model intercomparisons projects such as ROSE (e.g. (Luderer et al., 2016)) and LIMITS (e.g. (Aboumahboub et al., 2014; Kriegler et al., 2013) and ADVANCE (e.g. (Luderer et al., 2018)) confirmed that the timing of climate policy matters for long-term transformation pathways in global models. A **delay in the mitigation action** typically leads to increasing mitigation costs as more costly mitigation options needs to be used to compensate for the lost time and additional costs accrue to overcome potential lock-in effects into fossil-based technologies. Figure 63 compares global carbon prices for ADVANCE scenarios with delayed and early action. A delay in climate change mitigation efforts therefore tends to also increase the reliance on new carbon dioxide removal technologies (see Section 17.4.8.2). EU-level studies also confirm that a delay in climate action strongly impacts mitigation costs. Capros et al. find that EU carbon prices skyrocket across models if a delay in EU climate action until 2030 is assumed. In the case of further constraints of technology availability, carbon prices reach prohibitively high levels (Capros et al., 2014b).

Caution is required in interpreting the results due to a **potential selection bias caused by models running into feasibility issues for more ambitious scenarios** (e.g. typically associated with infinitely high carbon prices) not being represented in the data as these do not report carbon prices. For the more ambitious 1.5°C temperature target combined with delayed action, it can be seen that only very few models provide results – either due to infeasibility issues or due to models not running this scenario at all – making the carbon price ranges for delayed action seem comparably low. It is thus recommended to focus on comparing the carbon price estimates of the *same* model, not overall price ranges. Comparing to 1.5°C-early action carbon price estimates for the *same* models reporting both delayed and early action carbon prices shows lower carbon prices in 2030 for delayed action compensated by higher carbon price estimates for delayed action in later years, in line with what the literature suggests.

Studies assessing the impact of **fragmented action** on global mitigation costs typically find that policy costs are higher for fragmented efforts than in global cooperation scenarios (see e.g. IPCC AR5 WGIII report (Edenhofer et al., 2014)). This is confirmed by studies focusing on the EU and the macro-economic impacts for scenarios with concerted efforts of large emitters or with only the EU taking ambitious climate action (see Section 17.6.1.3 (Vrontisi et al., 2019) and Section 17.6.1.1 (European Commission, 2018a)).

Figure 63: Differences in Carbon Prices comparing ‘early strengthening’ and ‘delayed strengthening’ scenarios in ADVANCE



Note differences in the y-scales to improve readability. MESSAGE=MESSAGE-GLOBIOM. Note that IMAGE assumes a ceiling value for the carbon price of 4000 USD/tC (1090.91 USD/tCO_2). Note that IMACLIM and GEM-E3 only report results until 2050. Note a potential selection bias for 1.5°C scenario results due to potential infeasibility issues to produce results for very ambitious scenarios. Note that POLES assumes substantially higher population growth (see Appendix Figure 113).
Source: own illustration, Climate Analytics based on ADVANCE database (IIASA Energy Program, 2019).

17.4.3.7 Discussion

These common **storylines** and underlying input assumptions have the advantage of improving comparability of mitigation cost estimates across models. Using the same SSP as an input to different models allows to identify which differences in cost estimates can be attributed to model structure (see for a given stabilisation target. The common narratives meanwhile play an important role in Section 17.4.6) the scientific literature as well as for e. g. the upcoming Sixth Assessment Report of the IPCC. By outlining the diversity of possible future states of the world in form of a narrative (instead of bare numbers on e. g. GDP growth), the reader can choose which future he/she considers most realistic and how high the difference in costs would be comparing a more optimistic scenario to a more pessimistic scenario. Yet, it should be noted that the SSPs should not be misinterpreted as projections of likely future outcomes, because projections into the future – especially given the long-term perspective – remain subject to very high uncertainty. That is why there are no probabilities attached to those scenarios and there is also no best-guess scenario.

Moreover, while harmonised storylines improve comparability between model results, it should be noted that storyline assumptions such as the SSPs have a strong normative character as they involve assumptions on socio-economic trends and behavior, such as lifestyles and demographics. The decision which socio-economic assumptions about our current world and the future development are deemed most credible is therefore a normative choice, especially as the future world anticipated by these storylines is partly driven by factors that can be influenced by polices and societal transformation, such as

- Technological chance and innovation (see also Section 17.4.7.2 on 'technological change')
- Optimism or pessimism about techno-economic parameters such as the speed of ramping up of new technologies (see also Section 17.4.7 on 'Energy system detail and assumptions')
- Resource-intensive lifestyles vs. eco-friendly lifestyles (see also Section 17.4.8.3 on 'demand side mitigation')
- Inequality

Note, moreover, that though the storylines themselves are harmonised, the interpretation of the storylines and finally how these storylines are implemented in the model, especially with regard to techno-economic parameters, is at the discretion of the modelers and can lead to heterogenous interpretations.

In the ADVANCE database, the harmonisation on using the SSP2 (middle of the road scenario) without providing results for other socio-economic storylines, limits the possibility to explore the implications of alternative socio-economic developments.

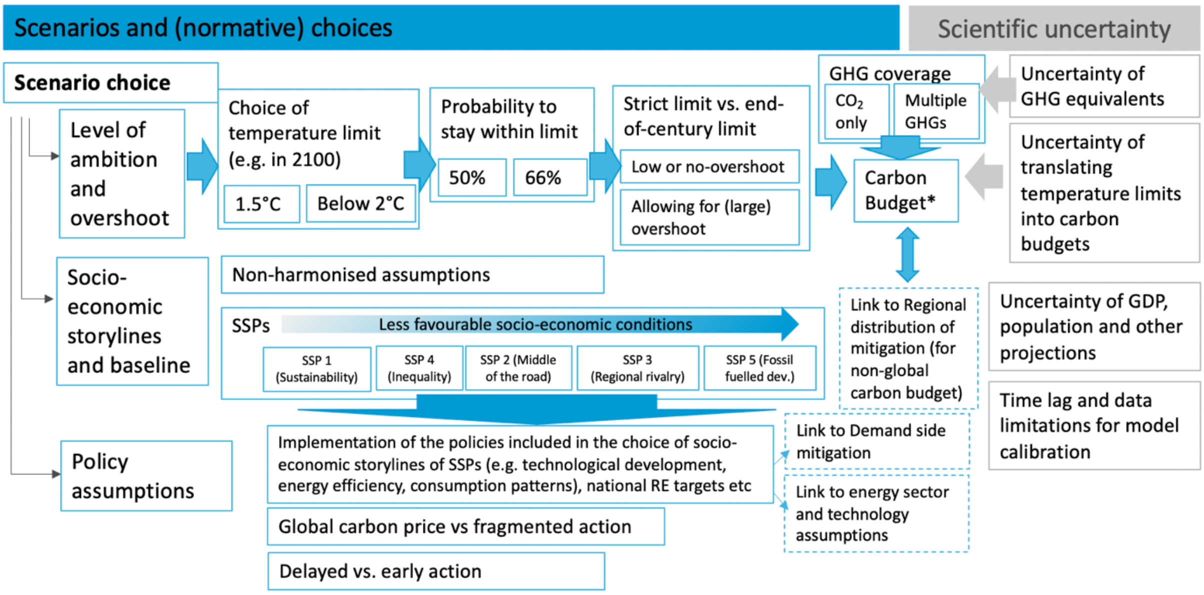
Moreover, it should be noted that potential impacts of climate change on GDP (damages) or population (death or migration) are not accounted for in the SSPs. It therefore remains crucial to be aware of this limitation when assessing different climate stabilization targets, as will be discussed below.

The question which **mitigation target** is considered socially acceptable is a strong normative choice. Since 2015, the Paris Agreement defines a clear benchmark for ambition setting the target of limiting global warming to '***well below 2°C above pre-industrial levels***' and '***to pursue efforts to limit the temperature increase to 1.5°C above pre-industrial levels***' (Article 2a, UNFCCC 2015). This means that the political debate has identified these targets as the commonly agreed global mitigation target. Scenarios that refer to these temperature targets will thus be the main focus of our graphical analysis for the remainder of the report chapter.

As noted in Section 17.4.3.4, it is however important to be aware of differences in **temporary overshoot** between pathways referring to the same temperature target, especially for ambitious targets. Due to the temporary overshoot, scenarios with the same the same long-term climate stabilization goal are not necessarily associated with the same climate damages, e.g. increasing risks of crossing threshold for irreversible damages. In Cost-Effectiveness-Analysis, the damages from climate impacts are however not accounted for.[212]

Figure 64 illustrates the (typical) choices with regard to scenario input assumptions for mitigation cost models.

Figure 64: (Normative) choices and scientific uncertainty related to scenario input assumptions



*For a detailed discussion of factors affecting the carbon budget (A. Nauels et al., 2019)

Source: own illustration, Climate Analytics.

17.4.4 Discounting

17.4.4.1 Heterogeneity in the literature

For Intertemporal optimization or more generally aggregating costs over time, it is common practice to apply discount rates assuming a lower valorisation of future costs and benefits (see Section 5.1 for an overview on the different components of the discount rate).

[212] Ideally, when determining the temperature limit or carbon budget or other form of boundary conditions on emissions for the Cost-Effectiveness Analysis, these potential damages would be taken into consideration.

Discounting is recognized as a crucial factor for Social Costs of Carbon (see Part 2), but it receives less attention in the debate on the mitigation cost side. This may seem surprising given that the assessment of long-term mitigation pathways also needs to deal with comparing costs (and benefits) over a very long-time horizon that goes beyond that of common economic analyses. Models typically apply relatively high discount factors for assessing long-term mitigation pathways, with the choice of the discount rate directly affecting the mitigation pathways and investment flows and the resulting technology mix. As higher costs in the future get lower weight with higher discount rates, this can lead to favoring ***more expensive mitigation technologies in later years*** (e. g. relying on costly negative emission technologies in the second half of the century) as opposed to stronger near time action. The choice of the discount rate can therefore play a critical role for determining long-term transformation pathways and related mitigation costs, while – in contrast to Cost-Benefit-Analysis – it does not affect the mitigation target in CE-analysis.[213] The discount rate value can be defined exogenously, as for example in GCAM, IMAGE, and MESSAGE assuming a discount rate of 5% per year staying constant over time (Kriegler et al. 2015)[214]. In other models, the discount rate can depend on other model parameters. In REMIND, the calculation of utility is subject to discounting, assuming a pure rate of time preference (rho) of 3% per year and an elasticity of marginal utility of 1. Applying the Ramsey rule, REMIND yields endogenous interest rates of 5–6% in real terms for economic growth rates of 2–3% per year, highlighting that this is in line with the interest rates typically observed on capital markets.[215] In WITCH, the discount rate depends on the marginal productivity of capital. The pure rate of time preference (rho) decreases over time from 3% per year to 2% per year towards the end of the century (chosen to reflect historical values of the market interest rate).[216] Also in WITCH, the Ramsey rule plays a role in determining the discount rate, though Kriegler et al. highlight that the Ramsey rule is not perfectly matched due to the complex nature of the economic growth part of the model (Kriegler et al., 2015)[217]. In POLES-JRC, the time discounting factors that is applied to investment decisions comprises a discount rate and a sector-specific risk preference factor (Keramidas et al., 2017a). While not specifying the discount rate level in the POLES-JRC documentation Keramidas et al. 2017), Kriegler et al. state that the POLES discount rate is about 8% per year (exogenous and constant over time, but can vary across sectors and regions) (Kriegler et al., 2015)[218].

Moreover, results can be recomputed in net present values by 'undiscounting' (post-processing of results) for example, to obtain the average mitigation costs between 2030 and 2050. For this, the applied discount rate used for post-processing is mostly made transparent, e.g. as a note to the graph showing the results. For example, in the Fifth Assessment Report of the IPCC, figures comparing post-processed model results typically apply a discount rate of 5% per year (Edenhofer et al. 2014)

The IPCC's Fifth Assessment Report summarizes that - despite disagreement on the level of the discount rate, a "consensus favours using declining risk-free discount rates over longer time horizons" (Kolstad et al. 2014, page 211). Moreover, the AR5 claims that "an appropriate social risk-free discount rate for consumption is between one and three times the anticipated growth

[213] Allowing for overshoot, the discount rate can also affect the ambition level, leading to higher overshoot for higher discount rates as shown by Emmerling et al (2019).

[214] See Kriegler et al. Supplementary Material Excel table tab „cost measures" (Kriegler, Petermann, et al., 2015) (download under https://www.sciencedirect.com/science/article/pii/S0040162513002576#ac0005)

[215] See Model Wiki for REMIND – Macro Economy (IAMC wiki, 2020)

[216] See Model Wiki for WITCH – Macro Economy (IAMC wiki, 2020)

[217] See Kriegler et al. Supplementary Material Excel table tab „cost measures" (Kriegler, Petermann, et al., 2015) (download under https://www.sciencedirect.com/science/article/pii/S0040162513002576#ac0005)

[218] Supplementary material of Kriegler et al.

rate in real per capita consumption" (Kolstad et al. 2014, p. 211). A discount rate frequently used in IAMs and also used in the AR5 assessments in Chapter 6 of the IPCC WG III report is 5% per year (see e.g. (Kriegler, Weyant, et al., 2014). The Special Report on 1.5°C reports ranges for social discount rates in CE-studies to lie between 2 and 8% per year (partly varying over time and over sectors) (Rogelj, Shindell, et al., 2018).

17.4.4.2 Implications for mitigation costs and discussion

Due to the long-term horizon of mitigation costs pathways, the choice of the discount rate has a strong impact on the evaluation of mitigation policies and measures Kolstad et al. 2014). For instance, it has an impact on the average price/net present value cost estimates; Lower discount rates result in higher average prices/net present value costs, if prices/costs increase over time (Kriegler, Weyant, et al., 2014).

Table 25 shows carbon price ranges from the SR1.5 database for pathways with ambition levels 'lower 2°C' or more ambitious, comparing projected carbon prices for the respective year and Net Present Value carbon prices for the same year discounted with an annual discount rate of 5%. It shows that already in the nearer future (2030), the discount rate substantially reduced the NPV_{2020} valuation of the carbon price level shrinking to about 60% of the undiscounted carbon price. For longer time horizons, this is even more pronounced. The 2020-NPV is only 2% of the 2100 carbon price.

Table 25: Carbon prices in SR1.5 database comparing undiscounted and Net Present Value

Carbon price ranges, mean and median values for pathways in SR1.5 database categorised as 'lower 2°C' or more ambitious

	carbon price|2030	carbon price|2030 (NPV_{2020})	carbon price|2050	carbon price|2050 (NPV_{2020})	carbon price|2100	carbon price|2100 (NPV_{2020})
Max	6,050	3,714	14,300	3,309	43,323	874
Min	0	0	75	17	154	3
Mean	266	163	839	194	3,823	77
Median	148	91	470	109	1,935	39

For Net Present Value (NPV) calculation, an annual 5% discount rate is applied in the SR1.5 database, discounted to 2020. Carbon prices are in 2010USD.

Source: SR1.5 database IAMC 1.5°C Scenario Explorer and Data hosted by IIASA, release 2.0 (Huppmann et al., 2019)

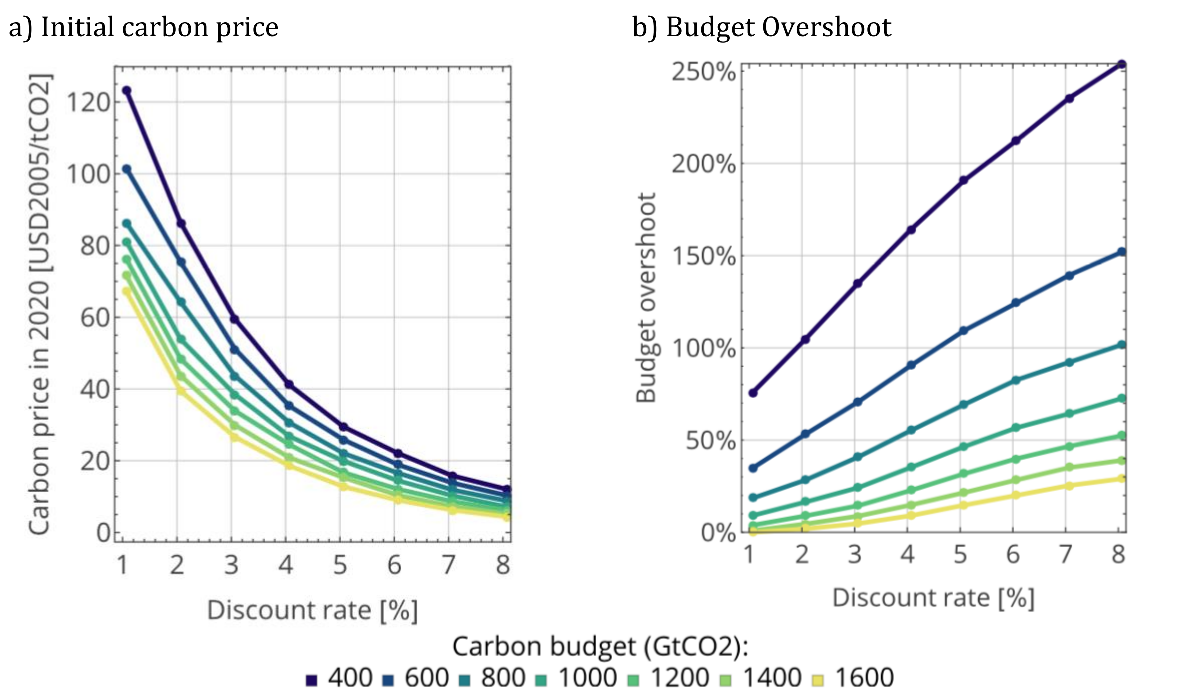
Though the critical role in directly impacting model outcomes and the contentious nature of assumptions on discount rates is acknowledged by the modelers, and generally discussed as for example in the IPCC assessment reports, information on the level and nature (e.g. subcomponents such as risk aversion) of discounting that is part of the model is typically rather hard to find and sensitivity analysis showing results for difference discount rates are scarce (as already noted by Goulder and Roberton discussing the role of discount rates for policy evaluation (Goulder & Roberton, 2012). Notable exceptions are (Kesicki, 2013) confirming that the choice of discount rate has an impact on Marginal Abatement Costs for the case of the UK and (Emmerling et al., 2019) assessing the impact of different discount rates on model outcomes using the WITCH model (Emmerling et al., 2019).

Emmerling et al. (2019) find that lower discount rates imply higher initial carbon prices and less overshoot of the carbon budget (see Figure 65). Moving from an annual discount rate of 5% to

2% for a 1,000Gt carbon budget (assuming that negative emission technologies such as BECCS and DAC are available[219])

- more than doubles the estimate for the initial (2020) carbon price from 21$/t$CO_2$ to 55$/t$CO_2$.
- increases the rate of growth in carbon price over time: For the same scenario the carbon price in 2100 is 289$/t$CO_2$ for a 2% discount rate while it amounts to 1093$/t$CO_2$ for 5% discount rate.
- more than halves the carbon budget overshoot (i.e. negative emissions needed) from 46% to 16%, corresponding to a reduction of about 300 GtCO2 of net negative emissions over the century. A 1 %-point increase in the discount rate results in up to a 50% increase in the overshoot.

Figure 65: Sensitivity of the carbon price and emission budget overshoot to varying discount rates in WITCH



Influence of the discount rate on the initial carbon price (a), and the carbon budget overshoot (b). Results from the WITCH model for the scenarios with full negative emissions availability (BECCS + DAC). The carbon price is expressed as carbon tax in 2020 expressed in USD2005/tCO_2. The carbon budget overshoot is defined as the cumulative net negative emissions (2011–2100) relative to the total carbon budget.
Source: Figure 1 d) and f) from Emmerling et al. (2019)[220].

Emmerling et al. (2019) also assess the implications of discounting for policy costs (in terms of GDP losses) and intergenerational justice using WITCH (see Figure 66). The study finds:

- For higher discount rate values future generations pay a higher share of the mitigation burden (absolute policy cost burden in current terms)

[219] BECCS- bioenergy and carbon capture and storage; DAC – direct air capture (see section 17.4.8.2)

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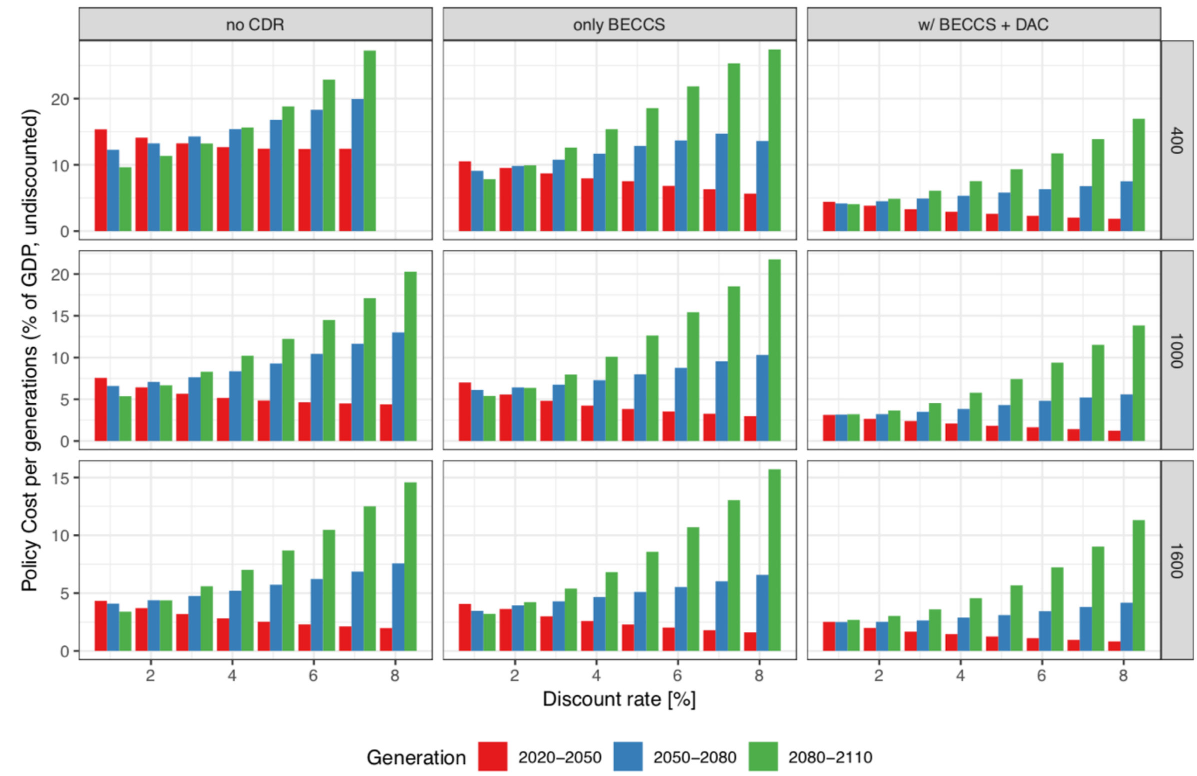
- For a 5% discount rate, the policy cost burden is about 4 times higher for future generations compared to a 1% discount rate
- More stringent carbon budgets reduce potential for intergeneration injustice (but at the same time have higher overall mitigation costs)
- Better availability of negative emission technologies increases the burden on future generations
- For a discount rate of 2-3% the mitigation efforts are equally distributed across generations independent of scenario and carbon budget

Figure 66: Intergenerational distribution of Policy Costs for varying discount rates in WITCH



Influence of the discount rate, the carbon budget and the availability of negative technologies on the policy cost of future generations. The total undiscounted policy cost, expressed as % of baseline GDP, of the three generations (living in 2020-2050, 2050-2080, and 2080-2110). No CDR: No Carbon Dioxide Removal Technologies available in model. Only BECCS: Bioenergy and Carbon Capture and Storage available, w/ BECCS + DAC: BECCS and Direct Air Capture available.
Source: Figure A.9 Supplementary Material (Emmerling et al., 2019)[221].

These strong implications for mitigation costs, budget overshoot and intergenerational justice raise the question whether it can be considered 'appropriate' to apply discount rates following 'market level' rates. Economic analysis suggests that risk-free, public, long-term interest rates need to be applied to the climate change problem. A survey of 200 experts on the appropriate level of (risk-free) social discount rate (SDR) finds that the surveyed experts consider a median SDR of about 2% and mean SDR 2.3% appropriate (with a range between 0-10%) (Drupp et al., 2018).

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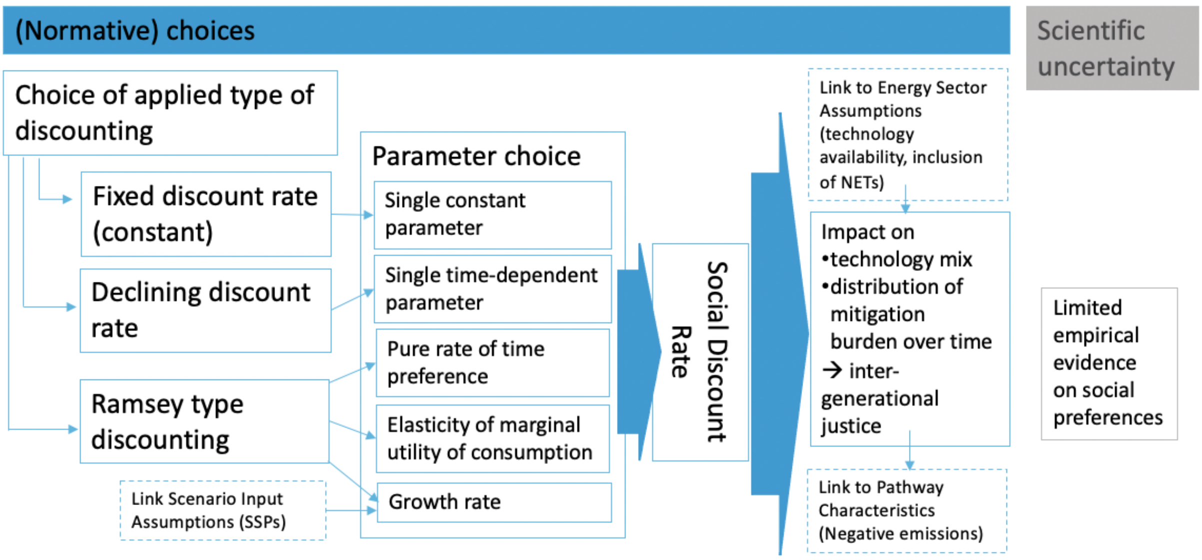
General justifications for applying non-zero discount rates have typically been the assumption that people tend to value future costs lower and that wealth increases over time and thus future generations will be wealthier than today's generation. However, it can be questioned whether the assumptions that wealth will continue to increase over time is realistic in the long run. Recent reports indicate that today's (or future generations) may not be much wealthier than past generations.[222] Taking climate damages into account as well, the expected burden on future generations would even be higher, as future damage costs may potentially be worsened by delayed action and carbon budget overshoot facilitated by higher discount rates. This burden is however not accounted for in Cost-Effectiveness-IAMs. Additionally, costs of mitigation are transferred to future generations who have not been responsible for historical emissions as discounting favours pushing mitigation costs into the future. Moreover, with discounting encouraging the application of costly and potentially risky backstop technologies, future generations are additionally burdened with the risk that these technologies either may finally not be technically viable or costlier than anticipated or may have risky side effects (see Section 17.4.8.2 on NETs).

As a consequence, scientists should be encouraged to a) be very transparent about the applied discount rate for cost assessments and b) to conduct sensitivity analyses for applying different discount rates, while policy makers should be aware of the underlying ethical implications of the discount rate choice.

Figure 67 illustrates that the choices related to discount rating schemes and parameters are mainly normative.

Figure 67: (Normative) choices related to discounting



Source: own illustration, Climate Analytics.

[222] E.g. a recent OECD study finds that income levels of the middle class have barely risen in many OECD countries over the past three decades (OECD, 2019).

17.4.5 Regional distribution of mitigation

17.4.5.1 Heterogeneity in the literature and in ADVANCE

Climate stabilization targets are defined globally as the atmosphere is a globally shared public good. When comparing **regional mitigation costs and their distribution,** it is therefore important to be aware of

- differences in regional disaggregation and how regions are defined in different models;
- differences in burden sharing (i.e. which region is assumed to contribute how much to achieving global emission reductions).

A more technical challenge of comparing regional cost estimates across models stems from **differences in the regional disaggregation**, i.e. the countries or regions that are explicitly modelled in the models**.** The definition of model regions may thus not be same across models, i.e. regions like 'Europe' covering different countries in different models.

Regional disaggregation in ADVANCE models

In the ADVANCE database, results are reported for the World and for five macro-regions[223]. The underlying level of regional disaggregation for the models participating is ADVANCE however, differs substantially as can be seen from the number of represented regions: MESSAGE-GLOBIOM (11), REMIND and IMACLIM (12), WITCH (14), AIM-GCE (17), IMAGE (26), GEM-E3 (37) and POLES (57). GEM-E3 and POLES are modelling different EU countries explicitly.

In the ADVANCE database, results are reported for selected individual larger countries. These are the EU28, China, USA, India, Russia, Japan and Brazil. However, due to the differences in regional disaggregation, these are not reported by all models.

A more fundamental aspect to be aware of are the challenges with regard to differences in assumptions on the **regional contribution to mitigation** and the resulting regional distribution of mitigation costs. Even under the idealized assumption that a global uniform carbon price is implemented, leading to reductions happening where they are cheapest, total aggregate economic cost mitigation would vary considerably between countries or regions in the absence of any transfer payments between regions. Relative aggregate costs in the OECD-1990-region under the described conditions (measured as a percentage change from, or relative to, baseline conditions), are found to be lower than the global average (Clarke et al., 2014). There are several reasons for these differences in relative regional mitigation costs:

- Costs are typically measured relative to an emissions baseline which typically means higher relative emission reductions in developing countries, thus leading to higher relative costs.
- Developing countries often exhibit higher energy and carbon intensities due to the structure of their economy, which induce higher economic feedback effects for the same level of mitigation.

[223] OECD90+EU: Includes the OECD 1990 countries as well as EU members and candidates. REF = Countries from the Reforming Economies of the Former Soviet Union. ASIA = The region includes most Asian countries with the exception of the Middle East, Japan and Former Soviet Union states. MAF = This region includes the countries of the Middle East and Africa. LAM = This region includes the countries of Latin America and the Caribbean.

- The costs for domestic mitigation are only one part of policy costs, another other part are impacts of abatement abroad on international markets. Fossil energy exporting regions would face higher costs due to unfavourable terms of trade effects of mitigation policy, while other regions with higher biomass potential could see increased bioenergy exports.

- Moreover, total costs (as opposed to costs measured as %-change relative to a baseline) as well as mitigation investments associated with these are also strongly affected by baseline emissions. Developing countries are typically projected to have higher baseline emissions.[224]

Importantly, the question how high regional mitigation costs are needs to be separated from the question **who pays the costs**. Different effort sharing schemes typically do not majorly affect the globally efficient level of regional mitigation, however, effort sharing schemes can considerably change who finances mitigation actions and required investments (Clarke et al., 2014). Imposing a burden sharing scheme, i.e. defining which region needs to contribute how much to global mitigation efforts, would induce financial transfers between regions (e.g. in form of buying emission allowances in a global Emissions Trading Scheme). Depending on the burden sharing schemes, this can substantially shift national carbon budgets and emission pathways and consequently mitigation costs (N. J. van den Berg et al., 2020).

Related to this question is the issue of **fragmented efforts**, i.e. when the mitigation target needs to be achieved by only a subset of regions participating while others remain inactive (see also Section 17.4.3.3 under scenario input assumptions). This can also be an important driver of mitigation costs. If major emitting countries refuse to participate in international efforts to curb emissions, this puts a higher burden on the willing countries and renders mitigation generally less efficient, i. e. costlier (see e.g. LIMITS project (Clarke et al., 2014) and (Kriegler et al., 2013)).

Regional Carbon Prices in the ADVANCE database

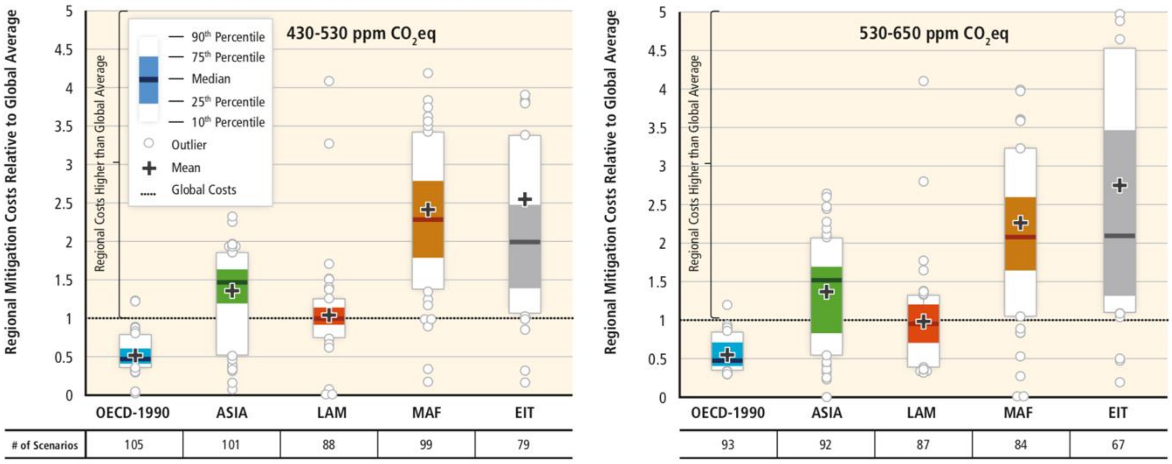
In the ADVANCE database, mitigation scenarios assume that a global carbon price is either implemented in 2020 ('early strengthening') or in 2030 ('delayed strengthening') as part of the scenario harmonization (see Section .4.3.3on harmonized scenario input assumptions and timing of action). This means that either from 2025 (for early strengthening) or from 2035 (delayed strengthening) regional carbon prices are in line with the respective global carbon price in most models in ADVANCE or converge to a similar level.

[224] The Kaya identity decomposes energy related emissions into the following drivers: population growth, per capita income growth, increase in energy intensity of economic output and in the carbon intensity of energy. Growth in population and income as well as energy intensity and per capita energy use are typically expected to be larger in developing countries, though exceptions have been observed. Thus, almost all *growth* in future baseline emissions is projected to be attributable to developing countries (Clarke et al., 2014).

17.4.5.2 Implications for mitigation costs

Regional mitigation costs can vary significantly. Figure 68 from the AR5 shows the relative mitigation costs for different regions for models in the AR5 database. These relative costs have been calculated as the cumulative costs of mitigation over the period 2020–2100 (discounted applying a 5% discount rate), divided by cumulative discounted economic output over that period. It can be seen that mitigation costs for OECD countries are generally considerably below the world average of mitigation costs for both stabilization targets. Figure 69 illustrates how regional mitigation costs in the AR5 vary depending on the model.

Figure 68: Relative regional mitigation cost estimates for two stabilization target ranges

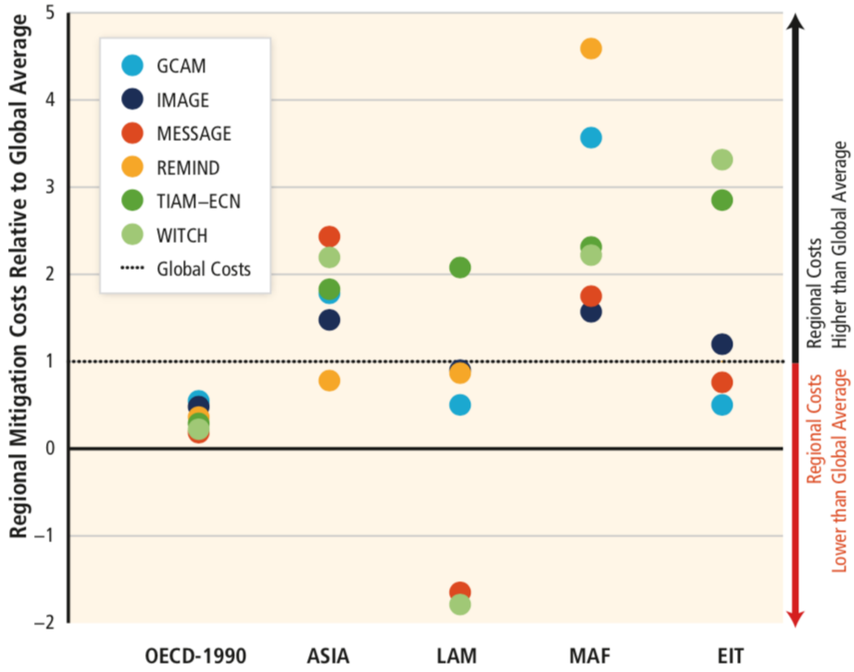


Regional mitigation costs relative to global average for scenarios reaching 430–530 ppm CO2eq in 2100 (left panel) and 530–650 ppm CO2eq in 2100 (right panel). Values above (below) 1 indicate that the region has relative mitigation costs higher (lower) than global average. Relative costs are computed as the cumulative costs of mitigation over the period 2020–2100, discounted at a 5% discount rate, divided by cumulative discounted economic output over that period. Scenarios assume no carbon trading across regions. The numbers below the region names indicate the number of scenarios in each box plot. [Added by the authors:] Regions: OECD-1990, ASIA, Economies in Transition (EIT), Middle East and Africa (MAF) region Latin America (LAM).

Source: Figure 6.27 from IPCC AR5 Chapter 6 WGIII (Clarke et al., 2014). Original source WGIII AR5 Scenario Database (Annex II.10), idealised implementation and default (see Section 6.3.1 of AR5) technology scenarios.

Figure 69: Relative regional mitigation cost estimates for different models

Results from the LIMITS model intercomparison project.



Regional mitigation costs relative to global average for a 450 ppm CO2eq concentration goal for a per capita effort-sharing scheme from the LIMITS multi-model study. Values above (below) 1 indicate that the region has relative mitigation costs higher (lower) than global average ones. Values below 0 are possible for regions who are large net sellers of carbon allowances. Mitigation costs are computed relative to the baseline, over 2020–2100 in NPV at a 5% discount rate. Emission allocations are based on linear convergence from 2020 levels to equal per capita by 2050, with per capita equalization thereafter. Regions are allowed to trade emission rights after 2020 without any constraint. LIMITS per capita scenarios. [Added by authors :] Regions: OECD-1990, ASIA, Economies in Transition (EIT), Middle East and Africa (MAF) region Latin America (LAM).

Source: Figure 6.30 from IPCC AR5 Chapter 6 WGIII (Clarke et al., 2014). Original source: WG III AR5 Scenario Database (Annex II.10 of AR5), LIMITS per capita scenarios.

17.4.5.3 Discussion of assumptions and 'tentative reality check'

Several of the underlying assumptions with regard to regional mitigation efforts and costs can be viewed critically.

First, the common assumption that a global carbon price is imposed in the models and that global markets will minimize overall mitigation costs by mitigating emissions where it is cheapest, can be viewed critical and is not reflecting political realities, market imperfections or other barriers.

Second, many IAMs apply Negishi-weights for regional welfare aggregation. This has been criticised as a strong normative assumption as it basically 'freezes' the current global income distribution between regions to avoid large transfers between regions that would result from a maximization of global welfare without this constraint (which would instead be leading to an equalization of income across regions)(Stanton, 2011).[225] This means that models applying Negishi weights provide policy recommendations that are based on the assumptions that global

[225] See also a recent working paper from (Dennig & Emmerling, n.d.) finding that Negishi weights distort regional inter-temporal preferences which has an undesirable effect on the discount rate and the savings rate (https://scholar.princeton.edu/sites/default/files/cfi/files/dennigemmerling.pdf)

income redistribution cannot and will not happen, while without the Negishi weight constraint in place models maximising global welfare would recommend that income levels should be (actively) equalised across regions as part of their policy advice (Stanton, 2011). Moreover, models applying Negishi weights tend to weigh consumption higher in already developed countries compared to developing countries.

Given differences in historical responsibility for GHG emissions as well as differences in capacities, the question who pays the costs has strong ethical implications. A meaningful regional mitigation cost estimate for achieving a certain mitigation target is thus always strongly dependent on considerations with regard to the overall global costs and needs to take considerations about financial transfers to other regions into account.

A Tentative reality check: Comparison of modelled emission shares with NDC pledges

To assess how well country-specific model results reflect current political realities of commitment to mitigation, we compare the regional distribution of mitigation effort resulting from the model estimates for 2030 to shares in global emissions resulting from the NDC mitigation pledges submitted to the UNFCCC for the Paris Agreement. This means that for each of the seven countries[226] for which specific results are reported in the ADVANCE database, we calculate the respective share in global GHG emissions (comprising all Kyoto gases translated to CO2-equivalents using the IPCC AR5 global warming potential factors, excluding LULUCF emissions). We then calculated NDC-benchmarks based on the Climate Action Tracker[227], in line with currently submitted NDCs[228]. To account for uncertainty[229] in projections of underlying macroeconomic variables, the CAT provides a range of GHG emissions (min/max) associated to each NDC. In this analysis, we focus on GHG emissions excl. LULUCF, in line with the Climate Action Tracker.[230] We compute the respective share in global emissions related to the NDCs and compare these NDCs' emissions ranges (relative to global 2030 emissions) with the model results from ADVANCE models for each of the seven countries reported in the ADVANCE database (EU 28, Brazil, China, India, Russia, Japan, USA)[231]. In 2030, these seven countries would be responsible for about two thirds in global emissions if NDCs are implemented as pledged.

In Figure 70, the regional shares in global emissions in the year 2030 from the ADVANCE database are graphically compared to the shares derived from NDC commitments for 2030. Overall, it can be seen that for China, the spread in estimated emission shares is much higher than for other countries, while the spread is very low for Brazil and Japan.

Moreover, it can be seen that for the EU28, the USA, Japan and Brazil, almost all model estimates predict a higher share in 2030- global emissions for these countries than what their respective NDC commitment would suggest, meaning that the countries – which are mainly industrialized

[226] Several IAMs in the ADVANCE database provide results for seven large economic aggregates or large countries such as China, India, EU, Brazil, Japan, Russia, USA. For simplicity, EU28 is here also referred to as "country" though comprising a union of countries, which however submitted a common NDC.

[227] https://climateactiontracker.org/countries/ (Climate Action Tracker 2019)

[228] As of September 2019.

[229] NDCs are of a diverse nature, e.g. referring to base year targets, business-as-usual targets or intensity targets, as well as including conditional and unconditional targets (For example, India's NDC has an unconditional NDC referring to emission intensity of GDP and a conditional NDC target on non-fossil fuel share in power generation capacity. We used the more ambitious conditional target here). As a consequence, NDC targets sometimes built on other macroeconomic variables, such as future GDP projections.

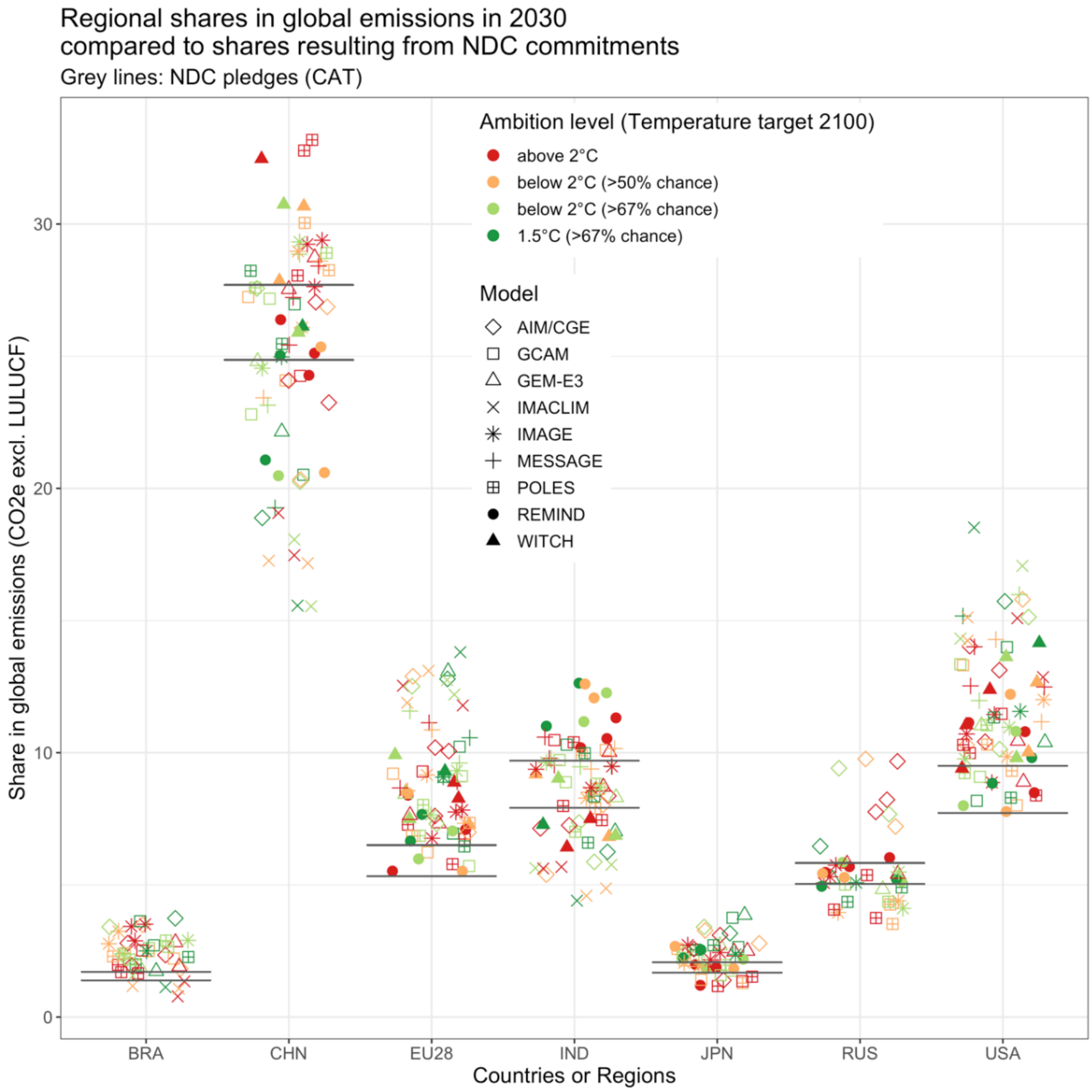
[230] For an explanation why the CAT excludes LULUCF from the NDC ratings, please see here: (Climate Action Tracker 2019a) https://climateactiontracker.org/methodology/indc-ratings-and-lulucf/

[231] Note that the US put forward an NDC target for 2025, instead of 2030. Therefore, in this exercise we use the "Obama mid-century strategy" to derive the emissions target for 2030. Note however that the US expressed their intention to withdraw from the Paris Agreement.

countries – politically committed to reduce their share in global emissions more than the models would estimate based on least cost considerations. This can be explained by several factors. As models search for the least-cost pathway, mitigation tends to happen in regions with a higher mitigation potential and lower average mitigation costs. For industrialized countries, average mitigation costs tend to be high. The NDC commitments, in contrast, also reflect political and ethical dimensions such as historical responsibility and e.g. financial capacity to contribute to mitigation efforts as well as political leadership.

Differentiating by models, it can be seen that results from IMACLIM for example tend to be furthest away from the NDC-emission shares for China, India, the EU28 and the USA, overpredicting shares in global emissions for the two industrialized countries and underpredicting shares for the two developing countries. Estimates based on the models IMAGE, POLES, REMIND and GCAM are mostly located close to the NDC-based emission shares, however, there is also a certain spread in the results from these models.

Figure 70: Comparison of NDC-related regional emission shares with results from ADVANCE (2030)



Note: Grey lines indicate ranges of emission shares in global emissions derived based on data from the Climate Action Tracker (CAT).

Source: Calculation based on data from Climate Action Tracker and ADVANCE database (IIASA Energy Program, 2019).

Generally, it should be noted that the results need to be taken with **caution and cannot be generalized** for several reasons:

- We only compared the shares for the year 2030 as this relates to the year most NDCs refer to. The regional distribution of emission shares in the pathways for other years may differ substantially, especially with negative emission technologies deployed in later years. Thus, the finding that a certain result reflects well the shares in global emissions in 2030 derived from NDCs can only provide an indication, but cannot be generalized to this pathway generally reflecting political realities well across time.
- Calculated country shares in global emissions derived from CAT-NDC-assessments are subject to high uncertainty due to diverse nature of NDCs and of uncertainty in underlying assumptions on future developments (e.g. GDP) or conditional NDCs. The resulting uncertainties can directly affect the country-specific calculation as well as the global emission estimates. Latest NDC updates are moreover not accounted for.
- NDCs are non-binding pledges which do not necessarily reflect actual developments and political efforts.
- The CAT excludes LULUCF emissions as these are highly uncertain. The main reason for this is that it is more difficult to keep track of emissions reduction in the LULUCF sector and projections can vary widely.[232] Thus, NDCs contributions considered here mainly focus on emissions from the energy and industrial sectors, while the picture for emissions including LULUCF may look very different.
- The graphs look at each region separately, however, the same pathway (and model) may lie close to the NDC emission shares for one country but may at the same time be far off for other countries.[233]

17.4.6 General model structure

Models differ in their general setup, including whether they cover the economy as a whole or focus on partial equilibrium analysis, in the way they represent the economy system and the foresight and solution mechanisms they apply. These will be scrutinized below.

17.4.6.1 Equilibrium type and economic system representation: Heterogeneity in the literature and in ADVANCE

At a very broad level, models can be classified by their **equilibrium type** differentiating between

[232] See e.g. for Brazil see for example the website of the Climate Action Tracker: https://climateactiontracker.org/countries/brazil/ (accessed Nov 19, 2020)

[233] We have calculated a tentative measure (not shown) to describe the overall fit of a Model-Scenario combination for all seven countries calculated by using the respective deviations (in absolute terms) of the model emission shares from the NDC-based emission shares and then averaging across all seven countries. It can be seen, that IMACLIM exhibits the highest average deviation of estimated regional emission shares from NDC emission shares in 2030 for all scenarios, followed by MESSAGE. IMAGE, POLES and REMIND exhibit the lowest average deviations in the ADVANCE database. Not surprisingly, deviations in most models are higher for the early action scenarios and highest for the most ambitious 1.5°C 'early action' Scenario. These assume that a global carbon price is implemented in 2020 already, which would lead to a shift in the distribution of regional emissions based on least-cost considerations of the models from 2020 onwards.

- **Partial Equilibrium (PE) models:**
    - Models that focus on a certain sector (mainly energy system models)
    - Objective function: minimize energy system costs
    - Commonly reported mitigation cost metrics: Additional Total Energy System Costs, Area under the MACC
- **General Equilibrium (GE) models:**
    - Models that cover the whole economy (e.g. CGE models and Optimal Growth models)
    - Objective function: maximize welfare (typically consumption)
    - Commonly reported mitigation cost metrics: GDP loss and consumption loss relative to baseline

PE models in the context of climate change mitigation typically have a detailed representation of the energy sector, while they treat the rest of the economy exogenously. Thus, PE models do not include the economy-wide feedback on energy prices and disregard interlinkages between the energy sector and rest of the economy. PE models typically maximise consumers' and producers' surplus or minimise operation and investment costs of represented sectors over time to meet a given (price-elastic) energy service demand. Bottom-up energy system models as discussed in 16.2.2.3.1 (MARKAL, POLES, TIMES, GENeSYS-MOD) and some CE-IAMs likeIMAGE may be assigned to this category. GE models on the other hand, cover the whole economy with a more or less detailed representation of specific economic sectors. Several top-down macroeconomy models including CGE models and hybrid type models as discussed in 16.2.2.3.2 as well as some IAM models like REMIND, and WITCH are examples of General Equilibrium models.

However, the categorization into Partial and General Equilibrium models is not always straightforward, as some IAMs combine PE and GE features in their model suite.[234] For example MESSAGE-GLOBIOM links energy engineering and land-use partial equilibrium models to a macro-economic general equilibrium model. For GCAM, the classification in ambiguous. While Kriegler at a.l (2015) classify GCAM as Partial Equilibrium model, other sources assign it general equilibrium patterns.[235]

Less common are „non-equilibrium models" such as E3M3 which have a different underlying macro-economic theory being "Post-Keynesian" (Mercure et al., 2019). They relax assumptions on clearing markets and optimal resource use due to price signals and allow e.g. for unemployment and idle capacities. However, also here the distinction is not so clear cut with models such as IMACLIM and GEM-E3 also allowing for certain market imperfections. We follow the categorization typically used in the literature.

[234] IAMs are typically a combination of different models that are either hard-linked or soft-linked (see section16.2.2.3.3).

[235] For example in its ‚score card' in the IAMC model wiki, GCAM assigns itself to have some General Equilibrium features, (see https://www.iamcdocumentation.eu/index.php/Reference_card_-_GCAM), while neither being a CGE model nor an Optimal Growth model. We therefore follow the classification of Kriegler at al. (2015).

Equilibrium types in the ADVANCE database

- General Equilibrium models: AIM/CGE, GEM-E3, IMACLIM, REMIND, WITCH, MESSAGE-GLOBIOM[236]
- Partial Equilibrium models: GCAM[237], IMAGE, POLES

The equilibrium type is moreover linked to the **representation of the economic system**. Models differ with regard to the granularity to represent economic system and interactions between various economic sectors:

- Taking ***economic activity as an exogenous parameter***, as typically done in Partial Equilibrium models.
- Having a ***simplified aggregated representation of economic system***, as typically done in Optimal Growth General Equilibrium models.[238] This typically means that there is no distinction between different economic agents (households, firms, governments, banks, or other monetary authorities) and no explicit modelling of different productive sectors (such as industry or services).[239]
- Exhibiting a ***detailed, multi-sector representation of economic system***, as typically featured in CGE-type General Equilibrium models. These can also be dynamic.

Categorization of economic system representation in the ADVANCE database

- Economic activity as an exogenous parameter: GCAM, IMAGE, POLES
- Simplified aggregated representation: MESSAGE-GLOBIOM, REMIND, WITCH
- Detailed multi-sector representation: AIM/CGE, GEM-E3 (dynamic), IMACLIM (dynamic)

Figure 71 shows the general structure of a cost-effectiveness Optimal Growth-type model with a simplified representation of the economic sector using the example of REMIND. It shows that in REMIND that other sectors that are not explicitly modelled in other sub-modules are aggregated into a generic macro-economic sector represented by the generic aggregated 'output'. The production of the single good used for both consumption and investment is determined through a Constant Elasticity of Substitution (CES) function with capital, labour and energy services as input factors. The distribution of output across consumption, investment in physical capital and

[236] The categorization of MESSAGE-GLOBIOM is not straight forward as it links energy engineering and land-use partial equilibrium models to a macro-economic general equilibrium model.

[237] We follow the classification of Kriegler et al. (2015).

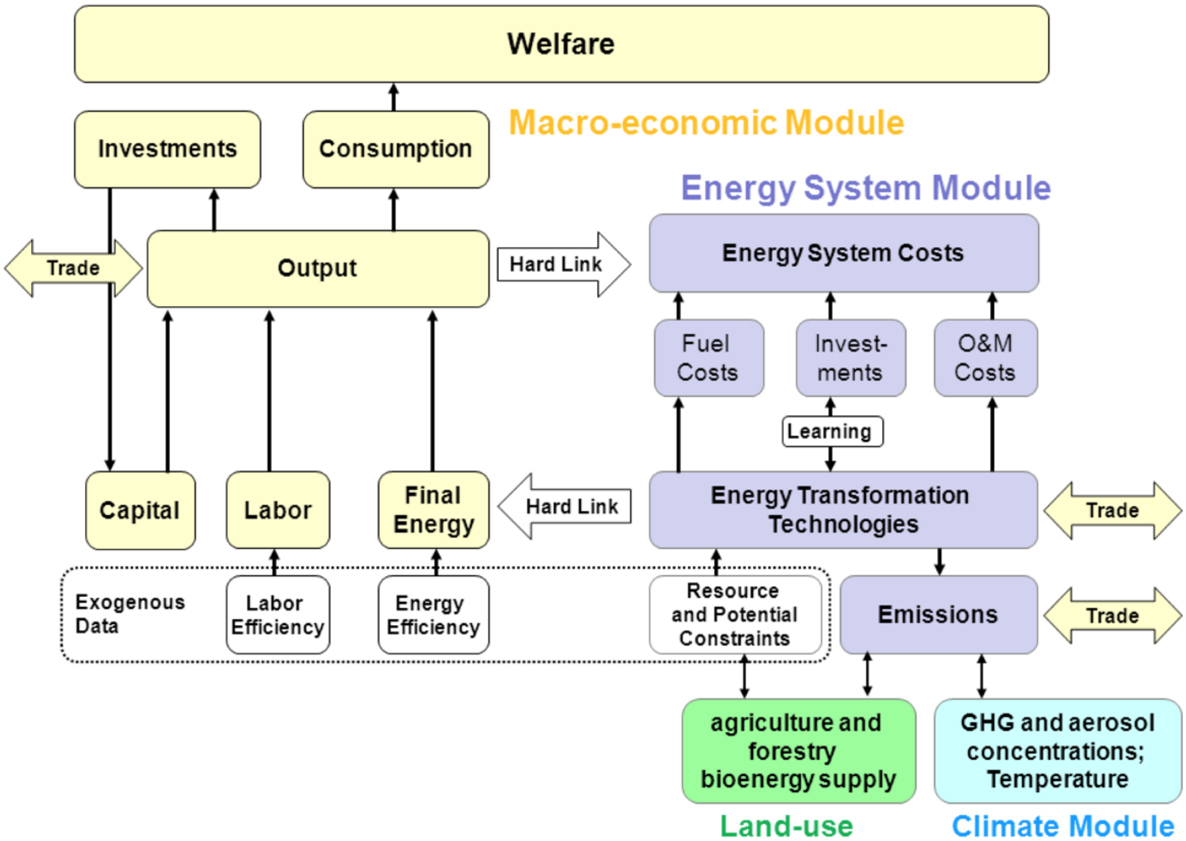
[238] The integration of energy system models with macro-economic growth models can be based on two main approaches: the "hard-link" or the "soft link" approach. The "hard link" approach integrates the full energy system model into the macroeconomic growth model as an additional set of functions and constraints and solves one very complex non-linear programming (NLP) problem. In the soft-link approach, both models are solved in isolation and information is exchanged between them in an iteration process. This is done by integrating a reduced form of the energy system model consisting of a set of static energy supply functions into the macroeconomic model, which results in a less complex model. An iterative procedure adapts the parameters of the reduced form model until the changes of the energy demand paths get sufficiently small. While the solution obtained with a hard-linked model is consistent, the soft-link approach only approximates this solution because it relies on a reduced form of the energy system model (Bauer et al. 2008a). Both REMIND and WITCH models belong to the sub-class of IAMs favoured in this respect as they hard link a detail energy system model with the macroeconomic growth model. Thus, they provide a general equilibrium structure that allows a more detailed analysis of some of the macroeconomic variables involved in climate change policies.

[239] Models can again be coupled with other models explicitly representing certain sectors such as agriculture / land-use that would otherwise be part of the aggregated economic representation, e.g. as in REMIND-MagPIE.

other energy expenditures is endogenously determined with assuming perfect foresight, maximising the sum of intertemporal discounted regional utilities, which in turn are represented as logarithmic functions of per capita consumption weighted by regional population. Different agents are not modelled explicitly. Similar structures can also be found in other Optimal-Growth-type global mitigation cost models such as WITCH.

Figure 71: Example of an Optimal Growth-type mitigation model with a simplified aggregated representation of the economic system (based on REMIND)

General Structure of the REMIND model



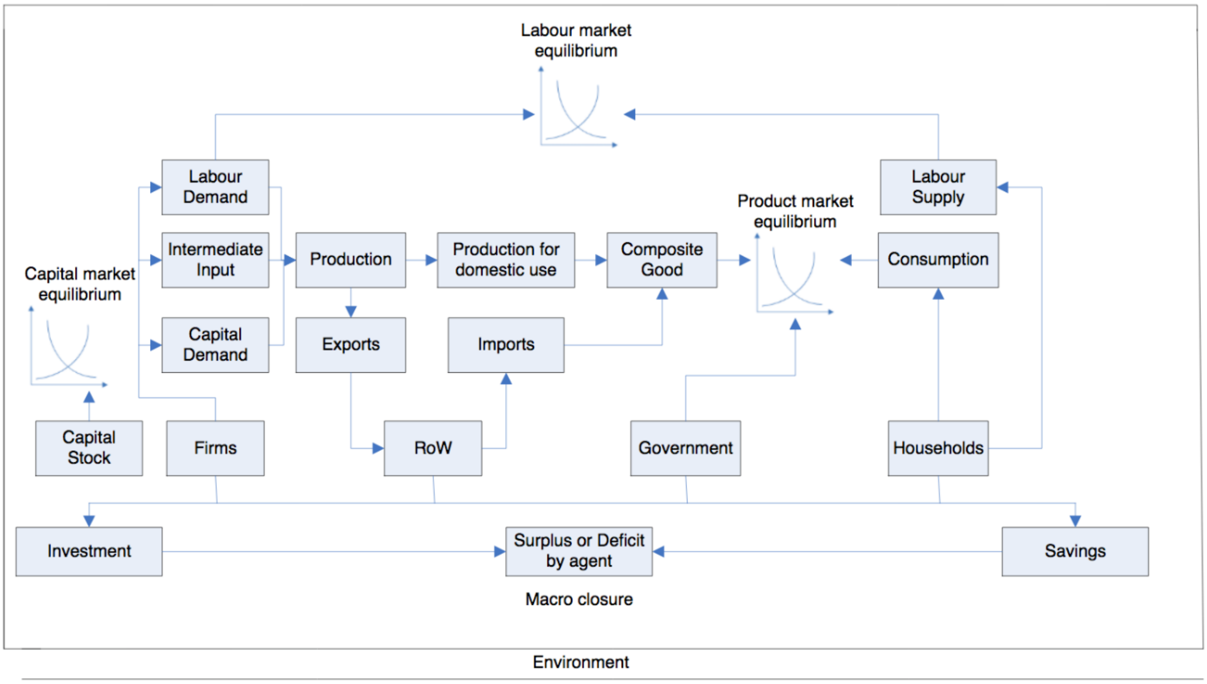
Source: Description of the REMIND model (version 1.6) (Luderer, Leimbach, Bauer, Kriegler, Baumstark, Bertram, et al., 2015) and PIK website (Potsdam Institute for Climate Impact Research, n.d.)[240]

Figure 72 shows the general structure of the GEM-E3 model to exemplify the structure of a typical CGE model with a detailed multi sector representation including the explicit modelling of different agents like firms, governments and households and their behavior as well as explicitly modelling different sectors beyond the energy supply, such as transport (air, land, water), chemical products, agriculture, construction and services (see GEM-E3 Model documentation 2017 (E3M Lab, 2017)).

[240] https://www.pik-potsdam.de/research/transformation-pathways/models/remind (last accessed Nov 12, 2020). Permission for usage of figure was kindly provided by Gunnar Luderer.

Figure 72: Example of CGE model with a detailed multi-sector representation of the economic system (based on GEM-E3)

General Structure of the GEM-E3 model



Note: RoW = Rest of the World

Source: Figure 1 from GEM-E3 Model documentation of the EU's Joint Research Center (Capros et al., 2013).

Moreover, models vary in the way they represent end-use sectors (for example the industry, transport or buildings sector), as well as in their representation of the land-use sector or aspects related to trade (see Section 17.4.11).

17.4.6.2 Representation of mitigation policy instruments

As consequence of the described differences in the representation of detail and actors, models also differ in their ability to represent **mitigation policies beyond carbon pricing**. Some models allow explicit modeling of **policy instruments design** for mitigation such as efficiency standards or support measures for specific (low carbon) technologies, which may also be part of the baseline (existing policies), socio-economic storylines or policy scenarios. The analysis of these kind of policies is typically playing an important role in regional or national models, in which the carbon price is typically not the main driver for emission reductions (see Section 17.6 on EU or Germany studies). Making full use of **energy efficiency** potentials has been identified as an important factor for a successful decarbonisation in EU level or Germany-specific studies, suggesting a need for policies targeting energy efficiency improvements (see e. g. (Fraunhofer Institute for Systems and Innovation Research ISI, 2015; Hartwig et al., 2017). Related to this are assumptions on demand side mitigation options (see Section 17.4.8.3).

For **carbon pricing**, the design of the **revenue recycling scheme**, i.e. how revenues from carbon pricing are redistributed, have also been shown to play an important role with regard to mitigation costs (see Section 17.6.1.3 ((Vrontisi et al., 2019)).

17.4.6.3 GHG coverage

The type of model can also be related to the **GHG coverage** of a model. As carbon emissions are the vast majority of overall GHG emissions related to energy, partial equilibrium energy system models may not represent other GHGs. Non-CO2 emissions, however, play an important role in other sectors like agriculture or air transport.

Due to for example differences in the GHGs' lifetime (how long they remain in the atmosphere) and a limited understanding of e.g. atmospheric processes, there is *scientific uncertainty* and an ongoing discussion around how to best convert non-CO_2 GHGs into CO_2 equivalents (see Section 17.4.11 on discussion on Global Warming Potentials).

Regarding the *impact on mitigation costs,* earlier studies have suggested that a multi gas approach allows more flexibility for mitigation ('what-flexibility'), reducing costs. For example, the meta regression finds that marginal abatement costs in studies assessing multi gas policies is almost 50% lower compared to studies that do not consider multi gases (Kuik et al., 2009a). However, abatement of non-CO_2 gases is typically found to be more challenging. Studies find for example that sectors like industry[241] and agriculture will likely be the main remaining sources of emissions in Germany by mid-century if decarbonisation of the power sector is successful (see e.g. Section 17.6.2.2 on national models).

Focusing on CO_2 emissions only may also be considered to have a policy prescriptive element as it puts low emphasis on the role of sectors which feature higher share of non-CO_2 emissions which are yet very relevant for ambitious mitigation efforts.

GHG coverage in the ADVANCE database

In the ADVANCE database, only IMACLIM has CO_2 only, all other models account for a broader range of GHGs.

17.4.6.4 Foresight and solutions mechanism

Another fundamental difference in the model set-up is the foresight and solution mechanisms that it assumes. There are two different approaches that can be differentiated:

- **Recursive dynamic approach:**
  - Decisions are taken based on the prices in the period of decision
  - Identifying market equilibrium for each time step
  - Referred to as *"myopic expectations"*
- **Forward looking intertemporal optimization approach:**
  - Decisions are based on expectations about all future periods, optimizing over the complete time horizon
  - Actors assumed to know exactly what will happen in the future incl. future mitigation options (technologies available) and prices
  - Referred to as *"perfect foresight"*

Optimal Growth (GE) models typically apply an intertemporal optimisation approach with perfect foresight. Intertemporal optimisation models focus on intertemporal dynamics of investment in production capital under perfect foresight about future production and consumption (e. g. MESSAGE-IAM, MERGE, REMIND, WITCH). Such perfect-foresight models

[241] Mainly parts of the industry sector that cannot be linked to the electricity sector.

perform optimisation over time assuming complete information is available over long time periods.

A dynamic recursive approach implies a myopic perspective, meaning thar actors do not know the future. It works by identifying a market equilibrium for each point in time based on exogenous assumptions about how production and supply sectors and the size of the economy evolve over time. Dynamic CGE models (as described in Section 17.4.6.1) typically apply the recursive dynamic approach. As a recursive dynamic model, savings and investment are based only on current period variables, as opposed to a forward-looking intertemporal optimisation model, where future economic conditions are assumed to be known with certainty. In GEM-E3 for example, planning for the future is based on current prices, solving sequentially over time in five year steps. For investments with longer lifetime GCAM for example allows actors to take future profit streams into account, however those estimates are also based on current prices.[242] Some models also allow to run in both modes, e.g. MESSAGE.

Categorization of models by Solution Mechanism in the ADVANCE database

- Perfect foresight/intertemporal optimization: WITCH, REMIND, MESSAGE-GLOBIOM
- Myopic/dynamic recursive: POLES, AIM/CGE, GEM-E3, IMACLIM, IMAGE, GCAM[243]

17.4.6.5 Implications for mitigation costs

The underlying differences in general model structures and assumptions also have implications for mitigation costs. A study by Guivarch and Rogelj attempting to quantify the relative contribution of model differences finds that – in their set of RCP2.6 scenarios from the SSP database – about 90% of the total variation in carbon prices could be explained by inter-model differences (Guivarch & Rogelj, 2017). This Section attempts to disentangle the inter-model differences looking into different aspects with regard to general model structures.

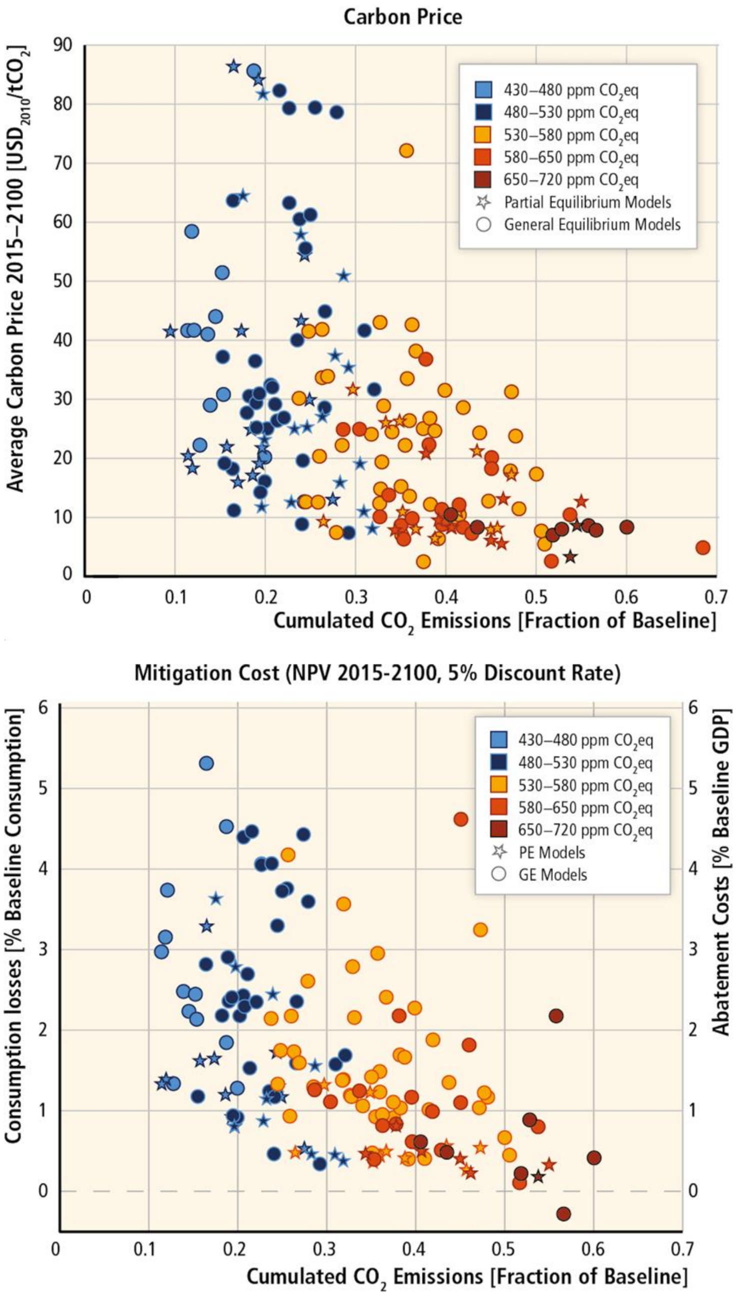
Aggregate economic costs tend to be higher in General equilibrium models than in partial-equilibrium models. Partial Equilibrium models without an explicit modelling of the economic sector (treating it as an exogenous parameter) tend to mainly represent direct financial engineering-oriented costs (e.g. costs for the energy sector) and neglect feedback effects on other sectors of the economy or resulting from other distortions. They tend to overlook higher level implementation barriers (such as capital constraints) and behavioral aspects, though exceptions exist.[244] Thus, they tend to yield lower mitigation cost estimate ranges (Söderholm 2012). This can also be seen in Figure 73 from the IPCC Fifths Assessment Report.

[242] See GCAM description in the model Wiki https://www.iamcdocumentation.eu/index.php/GCAM#Model_scope_and_methods.

[243] GCAM has been found to show exceptional behaviour with regard to carbon price trajectories for a model with myopic expectations. Guivarch and Rogelj explain that although being a recursive dynamic framework, GCAM exhibits exponentially rising carbon prices – for the SSP study scenario implementation – as the GCAM model was based on exogenous assumptions of carbon prices increasing exponentially to minimise discounted overall costs over the whole time horizon (Guivarch & Rogelj, 2017).

[244] Some partial equilibrium models explicitly include assumptions on barriers, for example the bottom-up simulation model FORECAST for the industry sector from Fraunhofer ISI (Fleiter et al., 2018).

Figure 73: Average Carbon price and Mitigation Costs comparing Partial Equilibrium models (PE) and General Equilibrium models (GE)



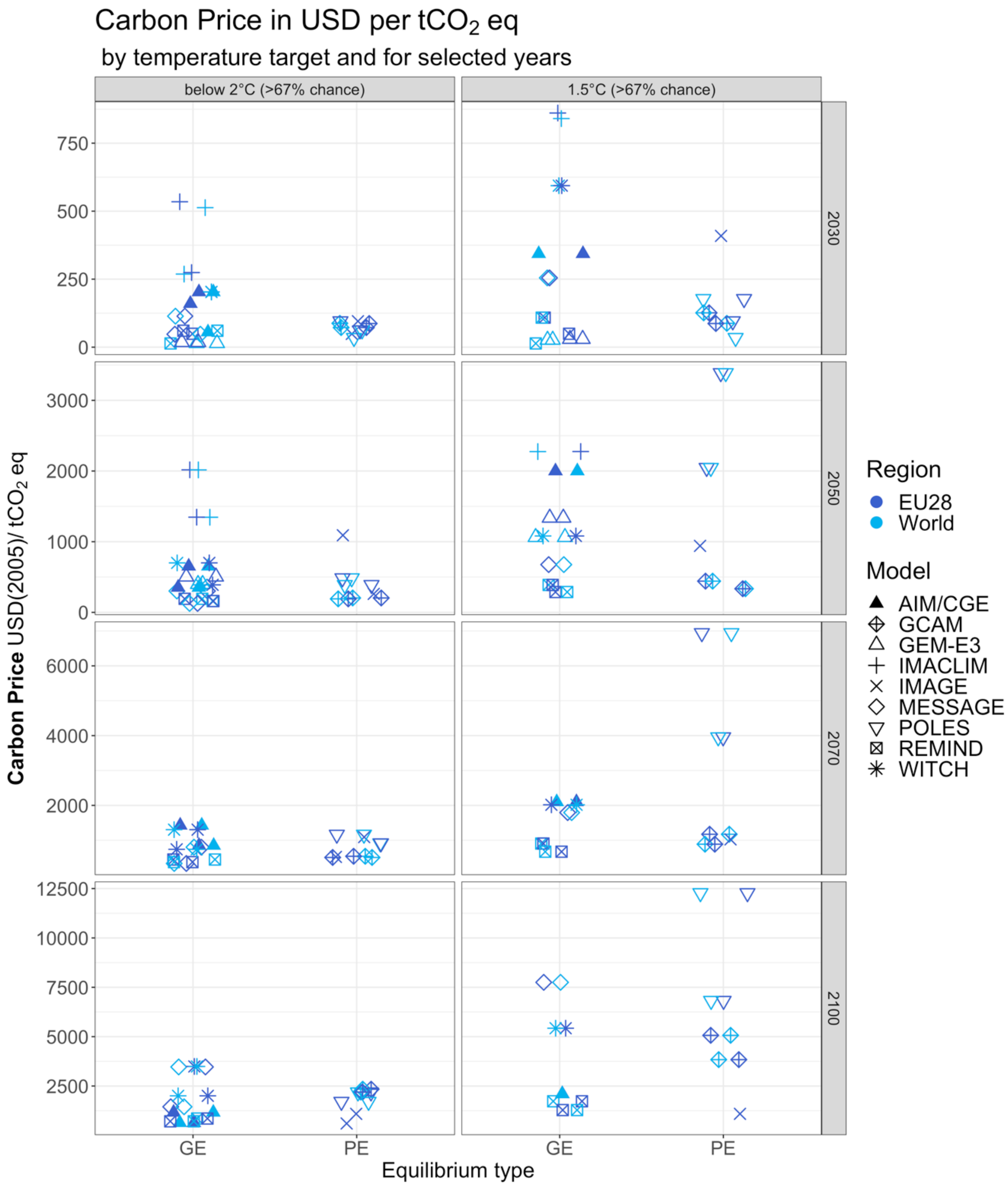
Average carbon prices (top panel) and global mitigation costs (bottom panel) as a function of residual cumulative CO2 emissions expressed as fraction of cumulative baseline emissions over the period 2011–2100. Emissions reductions relative to baseline can be deduced by subtracting the fraction of residual cumulative emissions from unity. Mitigation costs are reported in NPV consumption losses in percent baseline consumption for general equilibrium (GE) models and abatement costs in percent baseline GDP for partial equilibrium (PE) models. A discount rate of 5 % per year was used for calculating average carbon prices and net present value mitigation costs.

[Additional info on scenario selection from Figure 6.21 of AR5:] The scenario selection includes all idealised implementation scenarios that reported costs or carbon prices to 2050 or 2100 (only the latter are included in aggregate cost and price plots) after removal of similar scenarios (in terms of reaching similar goals with similar overshoots and assumptions about baseline emissions) from the same model.

Source: Figure 6.23 from IPCC AR5, Chapter 6 (Clarke et al., 2014). Original source: WG III AR5 Scenario Database (Annex II.10 of AR5).

Figure 74 based on the models in the ADVANCE database suggests that the finding that PE models typically report lower mitigation cost estimates than GE models seem to hold for the below 2°C temperature target as well as for the 1.5°C target, if the POLES model – which is exhibiting very high carbon prices - is considered an outlier (Note that POLES assumes substantially higher population growth (see Appendix Figure 113).

Figure 74: Carbon Prices comparing Partial (PE) and General Equilibrium (GE) models

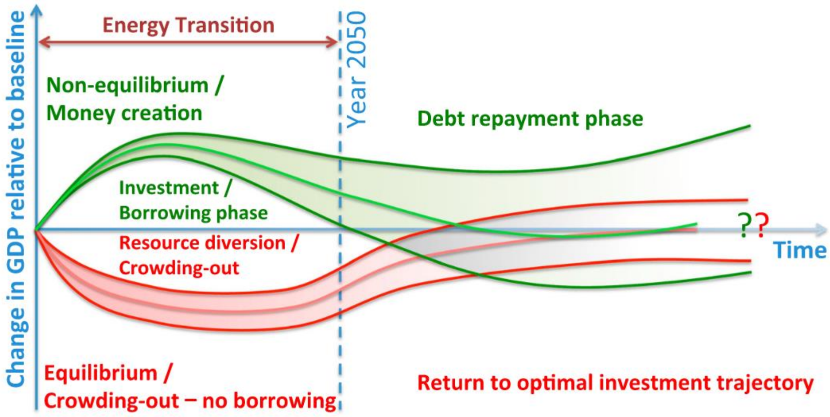


Note differences in the y-scales to improve readability. MESSAGE=MESSAGE-GLOBIOM. Note that IMAGE assumes a ceiling value for the carbon price of 4000 USD/tC (1090.91 USD/tCO_2). Note that IMACLIM and GEM-E3 only report results until 2050. Note a potential selection bias for 1.5°C scenario results due to potential infeasibility issues to produce results for very ambitious scenarios. Note that POLES assumes substantially higher population growth (see Appendix Figure 113).
Source: own illustration, Climate Analytics based on ADVANCE database (IIASA Energy Program, 2019).

Climate policy in equilibrium-based models per definition imposes macro-economic costs, while allowing for pre-existing inefficiencies can lead to gains. Partial and General Equilibrium model have in common, that they assume some form of (pre-existing) equilibrium. This however– per definition – leads to mitigation policy always imposing costs (e.g. in the form of **losses in terms of GDP or consumption)**, as the mitigation target imposes a constraint on the (optimally allocated) resources – leading to a deviation from the equilibrium. In contrast, models that relax assumptions of perfect markets and allow for unused resources and pre-existing inefficiencies can find positive GDP impacts of mitigation (Mercure et al., 2019). This is for example shown in the macro-economic analysis part of the Indepth Analysis of the European Commission (European Commission, 2018a) and the multi-model study for the EU (Capros et al., 2014b) (see Section 17.6 on regional models). The different underlying mechanisms are illustrated in Figure 75.

Figure 75: Illustrative comparison of GDP impacts for different economic schools of thought

Illustration of GDP changes (relative to a baseline) of a hypothetical policy-driven transition for models assuming equilibrium-conditions and "non-equilibrium" models



Note: Hypothetical example, assuming that the transition is financed (by borrowing or self-finance) from first time step until the vertical dashed line, after which low-carbon finance ends. Red line illustrates typical processes in equilibrium models, green line in non-equilibrium models. For original figure caption see footnote 245.
Source: Figure 2 from Mercure et al. (2019).[245]

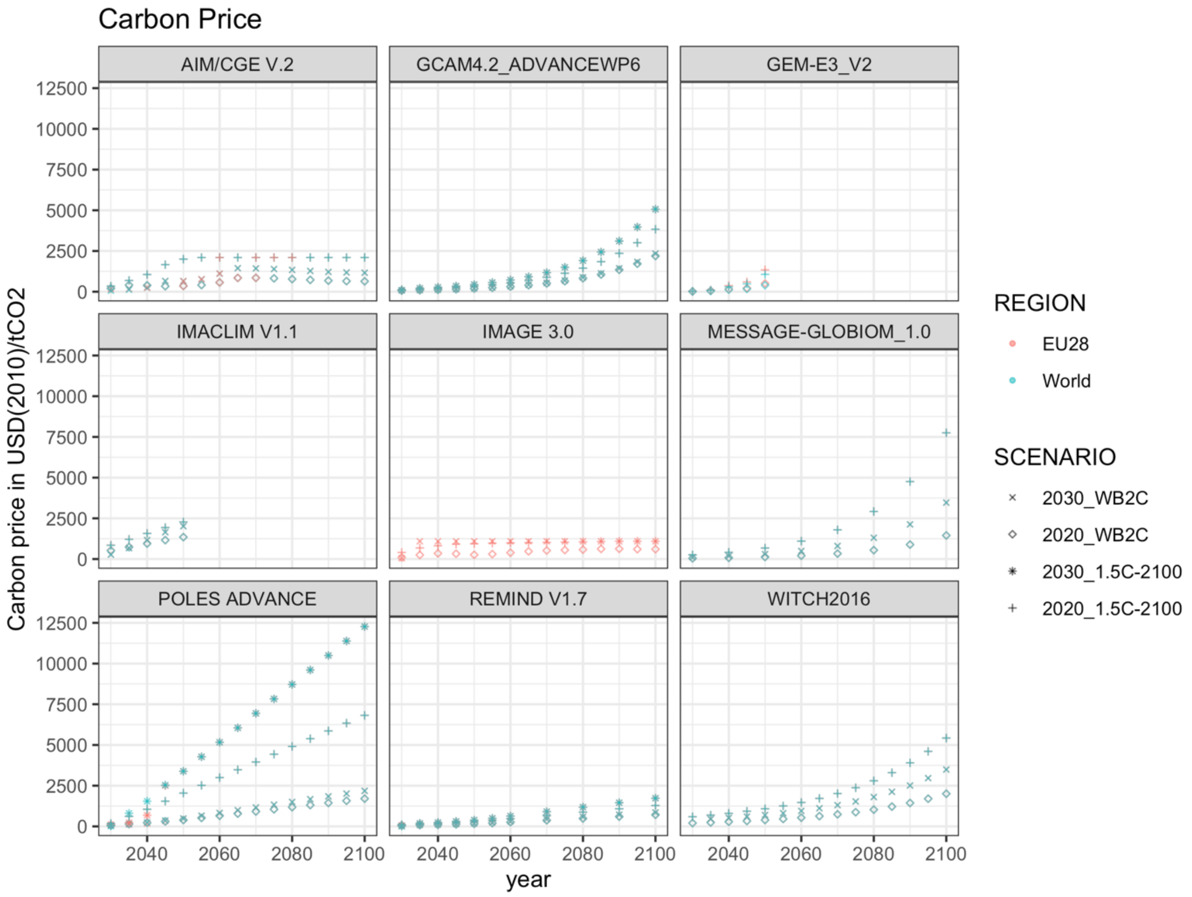
Optimal Growth models tend to yield lower carbon prices – at least for the shorter run – compared to (myopic) CGE models as they typically assume perfect foresight and do not reflect the same level of economy wide interactions and distortions that CGE models feature. However, intertemporal dynamics also differ, with perfect foresight (Optimal Growths) models typically exhibiting exponential growth in carbon prices over time. As argued in the previous section, the assumptions on the ***economic system representation*** and ***foresight assumptions*** are closely linked. CGE models with a detailed representation of the economic system typically assume myopic anticipation (recursive-dynamic). CGE models tend

[245] Open Access article allowing use under the terms of the Creative Commons Attribution-Non Commercial-No-Derivatives License (http://creativecommons.org/licenses/by-nc-nd/4.0/). Original figure caption: „Illustration of GDP changes, relative to a baseline, of a policy-driven sustainability transition for the two groups of modelling schools of thought, equilibrium and non-equilibrium, in the current state-of-the-art. In this hypothetical example, a sustainability transition is financed (self- financed or via borrowing) from time zero until the vertical dashed line, after which low-carbon finance stops (figure co-designed by the authors). It is to be noted that for equilibrium models, recovery post-transition is strongly related to innovation processes such as productivity change, which mitigate the negative effects. However, even without representations of learning-by-doing and innovation, equilibrium models may still display a recovery post-transition due to processes such as reductions in fossil-fuel imports. Meanwhile, without representations of debt burdens, non-equilibrium models would not likely display a convergence post-transition" (Mercure et al., 2019, page 1028).

to exhibit higher mitigation costs as they account for economy wide interactions and distortions. Optimal Growth models – which typically perform intertemporal optimisation and assume perfect foresight and perfect information - tend to yield lower carbon prices compared to CGE models. This can be explained by perfect foresight models allocating emission reductions more efficiently over time by optimizing over the whole time-horizon in contrast to the step-wise optimization of a recursive-dynamic approach. The assumption of perfect foresight implies that agents can anticipate shocks in advance and adjust investment and trade decisions prior to the actual shock, leading to lower aggregated Policy Costs (Weitzel et al., 2016). The Special Report on 1.5°C finds that recursive-dynamic approaches yield higher carbon prices in the short run, but for the long-run they show modest increases – while perfect foresight models performing intertemporal optimisation exhibit exponential price developments (Rogelj, Shindell, et al., 2018). Focusing on the EU electricity sector, (Gerbaulet et al., 2019) compare results for the same model for a 'reduced foresight' scenario (myopic expectations) and a 'free allocation carbon budget approach' (perfect foresight), finding that limited foresight leads to higher investments into fossil infrastructure (especially natural gas) ending up as stranded investments in later years, thus increasing mitigation costs (especially towards the end of the time horizon until 2050).

Looking at the Carbon Price trajectories over time from the ADVANCE database (Figure 76), it can be seen that models that assume perfect foresight (WITCH, REMIND, MESSAGE-GLOBIOM) exhibit exponentially increases in their carbon prices over time, starting out more moderate and while yielding relatively higher prices in the long run (while prices in REMIND remain comparably low). Models assuming myopic expectations typically show the opposite behaviour with showing relatively higher carbon prices already in the short term and more moderate increases in the long term. For the ADVANCE database, this expected behaviour is confirmed for IMAGE and AIM/CGE. For IMACLIM and GEM-E3 only providing estimates until 2050, this tendency is less visible. In POLES, carbon prices increase almost linearly with a relatively steep slope which may partly be explained by assumptions on higher population growth (see Appendix Figure 113). Also GCAM is an exception as although being a recursive dynamic framework, it exhibits exponentially rising carbon prices. Already in other studies, GCAM has been found to show exceptional behaviour with regard to carbon price trajectories for a model with myopic expectations. Guivarch and Rogelj explain that - for the SSP study scenario implementation – the GCAM model was based on exogenous assumptions of carbon prices increasing exponentially to minimise discounted overall costs over the whole time horizon (Guivarch & Rogelj, 2017).

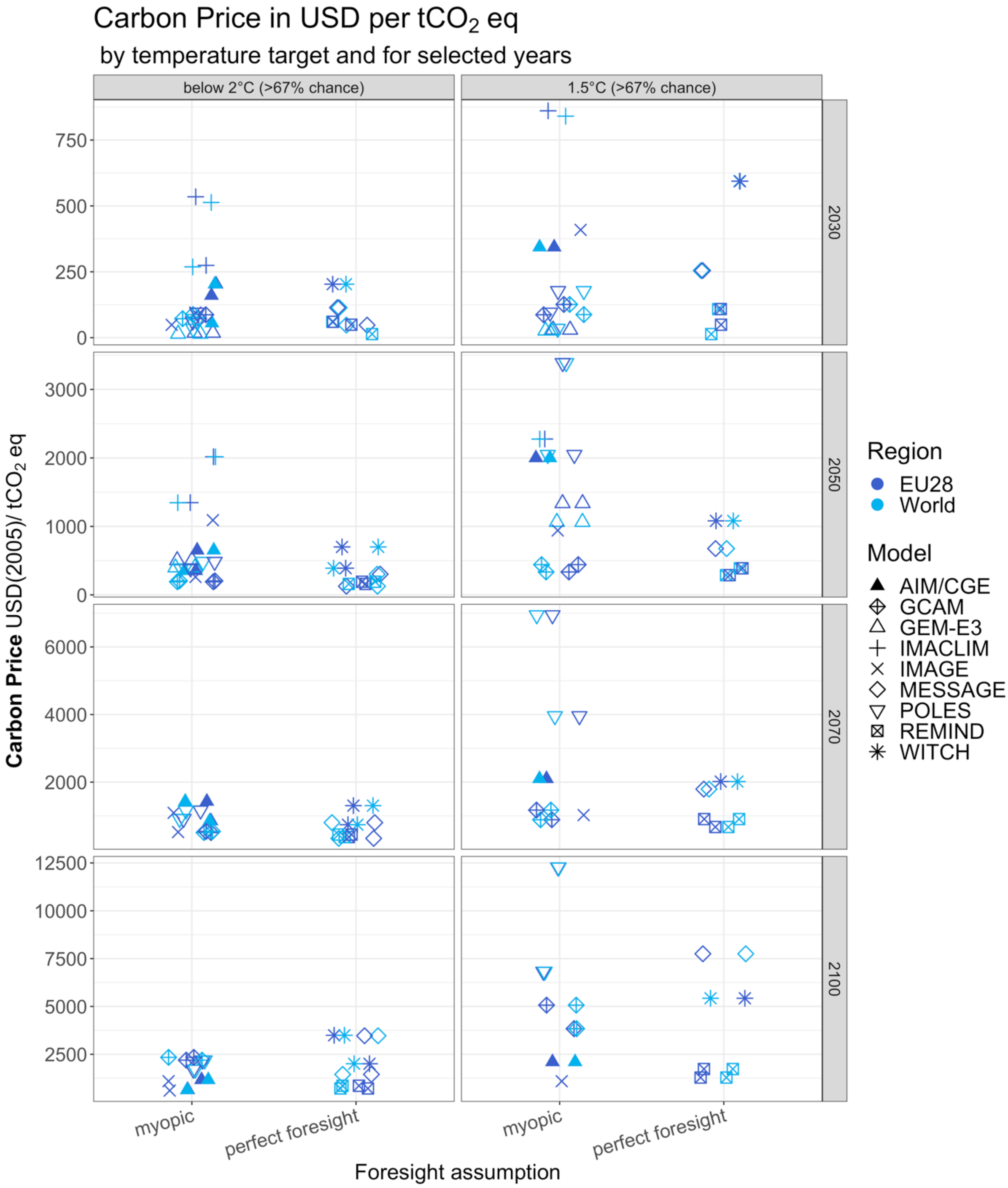
Figure 76: Carbon price trajectories over time by model (ADVANCE database)



Note that POLES assumes substantially higher population growth (see Appendix Figure 113).
Source: own illustration, Climate Analytics based on ADVANCE database (IIASA Energy Program, 2019).

Grouping ADVANCE models based on their assumptions on **solutions and foresight mechanisms** (see Figure 77), the findings from the literature are (weakly) supported, as the recursive-dynamic (myopic) models in the sample tend to exhibit lower carbon prices in earlier years compared to perfect foresight optimization models, while towards the end of the century this switches slightly – at least for the 2°C scenarios (while for the 1.5°C the picture is less clear). However, note that results are mainly driven by IMACLIM which is known for exhibiting high mitigation costs resulting from assumed market imperfections (e.g. partial use of production factors) and POLES which exhibits very high carbon prices.

Figure 77: Carbon Prices for different solution and foresight mechanism assumptions (ADVANCE)

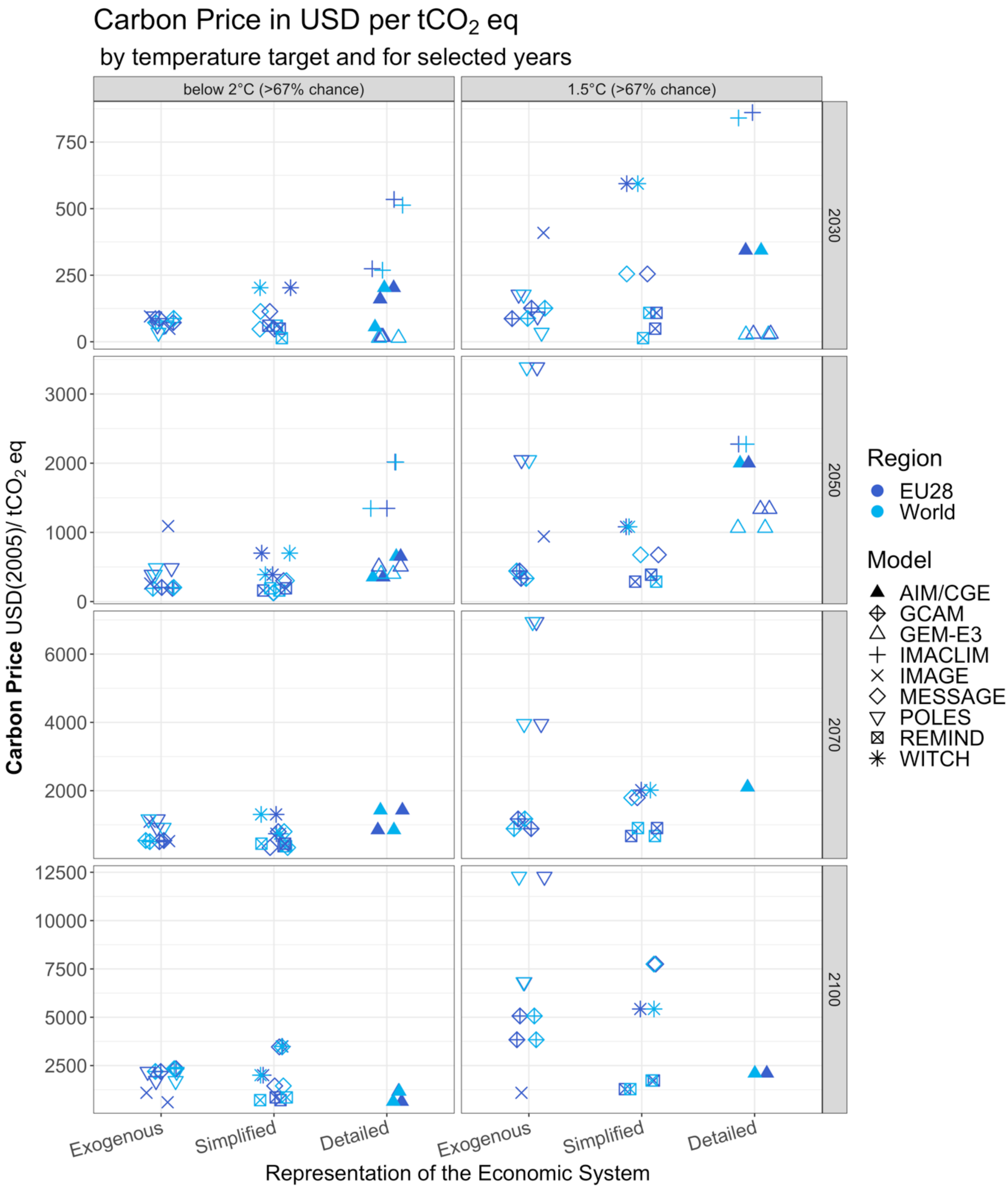


Note differences in the y-scales to improve readability. MESSAGE=MESSAGE-GLOBIOM. Note that IMAGE assumes a ceiling value for the carbon price of 4000 USD/tC (1090.91 USD/tCO_2). Note that IMACLIM and GEM-E3 only report results until 2050. Note a potential selection bias for 1.5°C scenario results due to potential infeasibility issues to produce results for very ambitious scenarios. Note that POLES assumes substantially higher population growth (see Appendix Figure 113).
Source: own illustration, Climate Analytics based on ADVANCE database (IIASA Energy Program, 2019).

Differentiating ADVANCE carbon price estimates by **representation of the economic system** (Figure 78), the picture is less clear. This is due to a variety of factors beyond the specific representation of the economic system, such as differing technoeconomic assumptions between models for mitigation technologies (see Section 17.4.7). In addition, this economic topology differentiation is inherently difficult as models in each category can include components within their framework normally found in the opposite – many models are hybrids to varying degrees.

Figure 78: Carbon Prices for different representations of the economic system (ADVANCE)

Marginal costs



Note differences in the y-scales to improve readability. MESSAGE=MESSAGE-GLOBIOM. Note that IMAGE assumes a ceiling value for the carbon price of 4000 USD/tC (1090.91 USD/tCO_2). Note that IMACLIM and GEM-E3 only report results until 2050. Note a potential selection bias for 1.5°C scenario results due to potential infeasibility issues to produce results for very ambitious scenarios. Note that POLES assumes substantially higher population growth (see Appendix Figure 113).
Source: own illustration, Climate Analytics based on ADVANCE database (IIASA Energy Program, 2019).

In an attempt to summarize the interplay of model characteristics by the model behaviour, Kriegler et al. classified different well-known global mitigation models to the categories 'high response', 'low response' or 'medium response' models depending on the respective model's behavior in response to carbon price signals following pre-defined carbon price trajectories (Kriegler, Petermann, et al., 2015).[246] Table 26 shows how the participating models have been classified by Kriegler et al. (2015).

Table 26: Classification of models into high-, medium- or low-response according to Kriegler et al. (2015)

Model	Classification
AIM-Enduse	PE – medium response
DNE21+	PE – low response
GCAM	PE – high response
GEM-E3	GE – low response
IMACLIM	GE – low response
IMAGE	PE – high response
MERGE-ETL	GE – high response
MESSAGE	GE – high response
POLES	PE – medium response
REMIND	GE – high response
WITCH	GE – low response

Source: (Kriegler, Petermann, et al., 2015).

Guivarch et Rogelj argue that this responsiveness should be transferable to carbon price levels resulting from imposing a certain mitigation target on the model, expecting that models classified as 'low response' would yield higher carbon prices and 'high response' models would exhibit lower carbon prices for the same mitigation target (Guivarch & Rogelj, 2017).

In fact, for REMIND, MESSAGE, GCAM and IMAGE, all classified as 'high response' models, we find comparably low carbon prices in the ADVANCE database for the first half of the century as can be seen in the figures above (for a comparison of carbon prices by model see also Figure 57 in Section 17.4.2.3). Towards the end of the century, carbon prices in MESSAGE and GCAM increase compared to the other models. WITCH, and IMACLIM – classified as 'low response' models – show comparably high carbon prices especially in earlier years. However, the picture is not always consistent. For example, POLES - classified as 'medium response' - exhibits the highest carbon price ranges after 2050 in the ADVANCE database. It should also be noted that

[246] For this, Kriegler at al. define different diagnostic indicators. A low response model shows (i) a low relative abatement index (this is an index measuring the emission reductions in a carbon price scenario relative to the baseline), (ii) a high CoEI (carbon intensity over energy intensity) indicator reflecting the relation of carbon and energy intensity reductions in response to the carbon price signal) and (iii) a low transformation index (reflecting the change in the energy mix due to the carbon price signal).

the model behaviour is not only driven by general model characteristics discussed in this section but also by other characteristics e.g. how the energy sector is modelled (see Section 17.4.7).

17.4.6.6 Discussion

The question remains which general model set-up can be considered to better reflect real world conditions Different model structures have their advantages which come along with different underlying simplifying assumptions that can be viewed critically.

Partial equilibrium models (treating the rest of the economy as exogenous) tend to represent the modelled sector with a high level of detail, however at the cost of representing only a narrow concept of mainly limited to the engineering perspective direct financial costs. At the same time they typically neglect costs and feedback effects on other sectors of the economy or from other distortions, leading to a risk of underestimating the true mitigation costs.

Optimal Growth models – typically coupling a detailed energy system model with an aggregated representation of the economic system based on a standard Ramsey-type growth model – account for feedback effects on the economy, however, the simplified representation of the economic system with one homogenous good does not allow a full capture of the real-world complexity and sector interactions or distortions. Optimal Growth IAMs mainly assume perfectly functioning markets with no frictions or transaction costs, which is not reflecting the real circumstances. Additionally, the assumption of perfect foresight about all future costs, policies and available technologies including their prices even for periods that are 80 plus years in the future is not in line with reality. The underlying assumption of a benevolent social planner conducting intertemporal optimization (over the whole economy) is also not realistic. Additionally, the lacking distinction between the different economic agents like households, firms and government, banks and other monetary authorities or different productive sectors such as agriculture, industry and services limits the possibility for analysing the economic interactions, while this can be performed at a more enhanced level by applying CGE models. One example is the implications of carbon pricing. A carbon price induces fiscal flows, usually from the private sector (e.g. from energy-intensive industries) to the government. Rising carbon prices thus could have strong impacts on the rest of the economy and the behavior of economic agents. However, the high degree of aggregation of economic systems as typical setting within most of hybrid-type and IAM models, does not allow a detailed investigation of fiscal effects, as no clear distinction is made between taxpayers and tax receivers.

CGE models have the advantage of taking the economy wide interaction effects and distortions into account and typically model different actors explicitly, aiming to represent real world complexity. However, this comes along with necessary limitations to reduce complexity in other areas.[247] For example, CGE models typically apply a dynamic recursive approach of step-wise optimization instead of intertemporal optimization. This implies that agents cannot adjust their behavior (investment or consumption decisions) in anticipation of future policies, price changes or shocks. While this may be seen as more realistic than assuming perfect foresight over the time horizon of 80 plus years, the reality is potentially somewhere in between. In reality, investors have expectations about future price developments and policies (though not knowing them with full certainty). Moreover, CGE models tend to be based on (often static) assumptions about the interaction between sectors typically derived from historical data and lack a sufficient detailed, technical representation of energy system. This limits their ability to model fundamental structural changes and to assess long-term transformational changes. On the other hand, the explicit modelling of sectors and economic actors (households, firms, government etc.) allows to

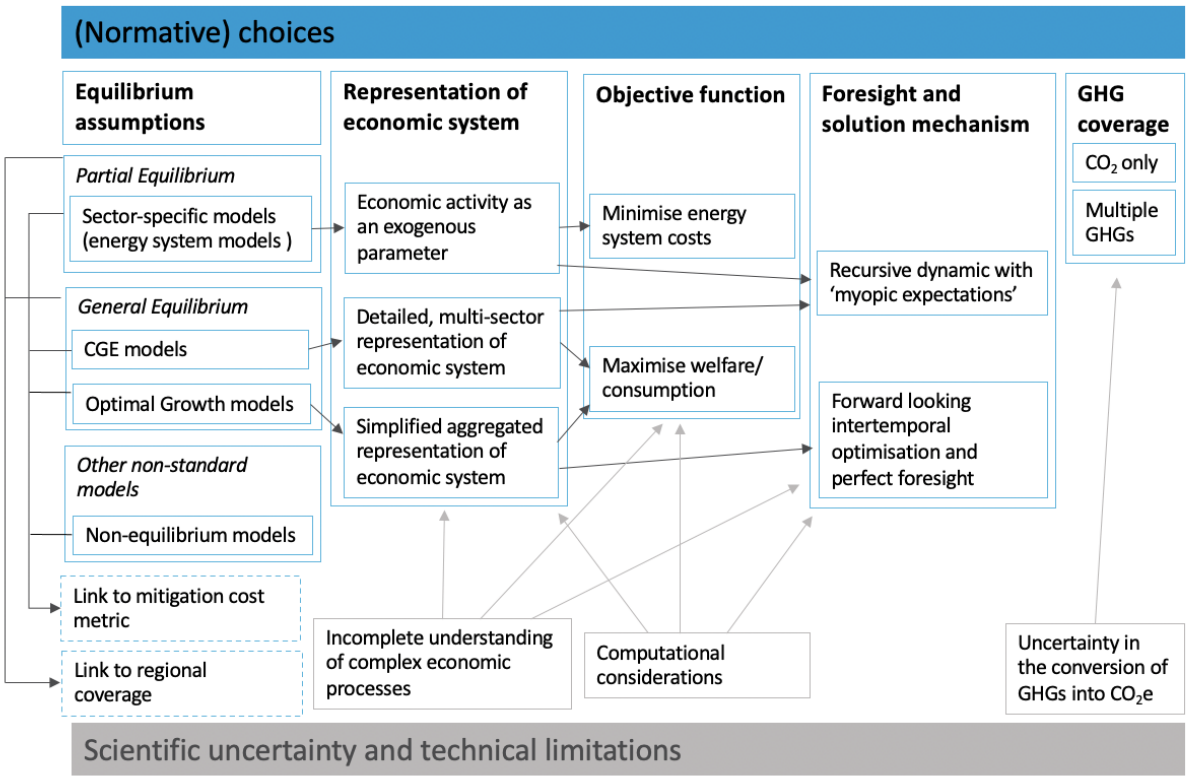
[247] Another typical simplification is that CGEs normally have a less explicit representation of the underlying energy system and cannot generally capture effects due to, e.g., vintaging and retrofits (see section 17.4.7).

analyse distributional effects as well which cannot be evaluated in aggregated representations (e.g. the winners and losers of certain policies).

Generally, it is important to keep in mind that most (global) mitigation cost models are designed to assess the solution to a global public good problem over a very long time horizon, mostly until the end of the century – for which no model can be expected to make assumptions, which fully reflect the reality; some simplifications are common in such complex modelling exercises. The purpose of CE-IAMs is thus not to provide (accurate) predictions. Rather, it is to capture the trade-offs and analyse interdependencies of complex systems under a variety of scenarios of future conditions. As a consequence, results need to be interpreted as holistic estimates as to the direction and magnitude of potential policies as well as spillover effects across system boundaries and tradeoffs with partly unintuitive feedbacks. A detailed representation of current sector interactions – as in CGEs - may also be considered to not be very useful and unrealistic to describe future economic structures, especially given the required profound structural change for the transformation process. Assumptions about details of the structure of the economy in 30 or more years from now can likewise be questioned as somewhat arbitrary. Optimal Growth-type CE-IAMs abstract from these details to derive information on 'the bigger picture' of potential long-term pathways under idealized conditions (e. g. perfect foresight, functioning markets, efficient climate policy instrument choice).

Figure 79 illustrates how the choice of model structures is related to fundamental model assumptions such as foresight and economic system representation, partly driven by technical limitations such as computational burden.

Figure 79: (Normative) choices and scientific considerations regarding general model structure



Source: own illustration, Climate Analytics.

17.4.7 Energy Sector and technology assumptions

17.4.7.1 Energy system details and assumptions

17.4.7.1.1 Heterogeneity in assumptions in the literature

Models vary substantially with regard to how the energy system is modelled and which restrictions are imposed. This can also vary based on the assumptions about the underlying SSP scenario (see Section 17.4.3.1). Given that the energy sector plays a crucial role in climate change mitigation and a successful decarbonisation of other sectors (such as transport) largely builds on a decarbonised energy sector (e.g. through electrifying transport), the energy sector is typically the core of models assessing long-term transformation pathways.[248]

Models differ greatly with regard to the following factors:

- Availability of (low-carbon) technologies and level of detail of technologies
- Imposed technical flexibility constraints
- Assumptions with respect to future cost of technologies

There are large discrepancies between models with respect to the **level of detail for the representation of technologies**, especially RE technologies. In general, the models represent a wider variety of renewable options in the electricity sector than in the non-electric sector. Although some models describe renewable energy (RE) technologies with a high level of detail, e. g., by distinguishing between multiple sub-technologies e. g. for wind and solar, other models with a stronger macro-economic focus only represent a few generic types of technology. Likewise, the level of detail in the representation of fossil technologies can differ greatly, with some models differentiating between multiple types of coal power plants (e.g. sub-, super- and ultra-super critical) and others featuring a single representative technology to represent how primary energy is converted to secondary energy (Krey et al., 2019). As a general tendency, GE models tend to include a lower level of technological detail compared to more energy-system-focused PE models for reasons of technical limitations. Compared to other Optimal-growth type models, REMIND and MESSAGE-IAM feature a higher level of detail in the representation of energy system technologies.

A more detailed, explicit representation of technologies variants allows for more explicit modelling of trade-offs between variants with better energy efficiency (and higher capital costs) and cheaper variants with lower efficiency (Krey et al., 2019). Generally, including more technology options provides larger flexibility to achieve emission reductions which typically reduces costs ('what flexibility'). One example of a key technology that has historically played a minor role in important global scenarios for energy is hydrogen; more recent studies began acknowledging the potential of hydrogen to be used as a fuel for transport, heating, energy storage, conversion to electricity and in industry (J. Quarton et al., 2020). Adequately representing technologies like hydrogen or storage technologies however, requires an detailed temporal and spatial resolution (J. Quarton et al. 2020), which is lacking in many models.

Additionally, models can cover a variety of **other supply and demand side mitigation options** that can deliver emission reductions in response to climate policy (see also Section 17.4.8.2 on 'Negative Emission Technologies' and Section on' demand side mitigation options'). Also, differences in the assumed lifetime or other techno-economic assumptions can be found for

[248] Typically, the energy system is modelled with the most detail. Some models also have a detailed representation of end-use sectors such as transport or buildings (see section 17.4.11).

different models and partly also for different regions within the same model (Krey et al., 2019). Models also differ with regard to their temporal resolution; e.g. how many time slices are modelled. A high temporal resolution is for example needed for assessing impacts on the stability of the power generation system and to model e. g. storage needs (batteries). However, more time slices come along with an increased computational burden. Thus, global models typically have low temporal resolution while regionally-focused models may include higher temporal resolution.

Models include **constraints in terms of technical flexibility** to switch from a fossil-fuel based technologies to low-carbon technologies:

- Constraints on premature retirement of capacities[249]
- Constraints on rapid ramping up of new technologies[250]
- Constraints on the flexibility of the energy sector technological mix[251]

These heterogenous assumptions affect a model's flexibility in response to implied mitigation policies. For instance, the study conducted by Bertram and co-authors indicated that models like MERGE-ETL have difficulty reducing emissions over 2030-2050, particularly in the electricity sector where no premature retirement of built capacities are possible (Bertram et al., 2015).

Pietzcker et al. (2017) describe how models (for six models participating in the ADVANCE model inter-comparison project) vary in their assumptions and ability to represent system integration with a specific focus on wind and solar (Pietzcker et al., 2017). A wide range of approaches to represent variability can be found in the models, ranging from (implicit or explicit) cost mark-ups to equations for flexibility and capacity, to time slices and residual load duration curves[252]. As variable renewable energy (VRE) technologies as wind and solar do not provide the same electricity over the whole year, this has implications for baseload. Including large shares of VRE in the system can lead to a reduced or even fully removed baseload, while the share of mid- or peak load stays high or even increases. However, not all global models differentiate between base-, peak- or mid-load. AIM/CGE, MESSAGE and WITCH do not differentiate between high and low load as they model electricity as a homogenous good. MESSAGE and WITCH then add flexibility constraints and a capacity constraint to force investments into mid-and peak load plants. These constraints mimic the increasing need for flexibility and potential requirements for back-up with higher VRE shares in the technology mix (Pietzcker et al., 2017). While WITCH applies fixed flexibility parameters for each technologies without representing much variation between regions, MESSAGE uses step-wise linear functions to model flexibility and capacity constraints which are fitted to the specific region (Pietzcker et al., 2017). In contrast, POLES

[249] For instance, unconstrained premature retirement was allowed (occurs when the market price does not cover operating costs) in earlier versions of DNE21+, GCAM, IMACLIM, MESSAGE, POLES and WITCH, while there was no premature retirement included in IMAGE and MERGE-ETL (Bertram et al., 2015). On the other hand, REMIND assumes that premature retirement of coal and gas-fired power plants before the end of the technical lifetime is possible, but is constrained to 4 % p.a. of installed capacity in the REMIND model (Luderer, Leimbach, Bauer, Kriegler, Baumstark, Giannousakis, et al., 2015).

[250] For example, in REMIND the rapid ramp-up of technologies has been subject to a cost penalty (i.e., "adjustment costs"), which scales with the square of the rate of change in new capacities (Luderer, Leimbach, Bauer, Kriegler, Baumstark, Giannousakis, et al., 2015).

[251] For instance, WITCH includes a constraint on the flexibility of the energy sector technological mix that penalizes excessive penetration of low flexibility technologies (i.e. renewables as well as base load technologies for example nuclear) versus high flexibility ones (i.e. gas power plants) (Bosetti et al. (2015)).

[252] These residual load duration curves are the residual load - temporally reordered – which still needs to be supplied by dispatchable technologies after generation from VRE has been subtracted from the load.

models residual load duration curves differentiating seven investment blocks derived from 'representative days'. REMIND and IMAGE directly implemented region-specific residual load duration curves which have been developed under the ADVANCE project, with REMIND using four and IMAGE using 20 load bands, thereby reflecting regional correlation between wind, solar and demand as well as the implications for investment into dispatchable power generation (Pietzcker et al., 2017). REMIND and MESSAGE (and WITCH but to a lesser extend) moreover also reflect a feedback effect that increasing the share of one VRE type will decrease its own market value as they use optimisation approaches. For models that do not perform optimization but instead use decision rules for investment it is more challenging to represent this feedback effect. To nevertheless represent this effect, model like AIM/CGE, IMAGE and POLES have implemented cost mark ups[253]. Models also represent expansion dynamics differently. AIM/CGE, IMAGE and POLES do not assume any constraints on how rapid the upscaling of a new technology can take place. In contrast, WITCH implements hard constraints with regard to the expansion rate which limits the growth rate of capacity additions compared to the previous time step. MESSAGE and REMIND apply soft constraints and non-linear adjustment costs increasing with the relative growth of capacity additions between time steps. This basically implies that the willingness to pay a cost mark-up can speed up the up-scaling of a new technology (Pietzcker et al., 2017). Model assumptions can also more generally impact the potential to show a structural shift. While AIM/CGE, IMAGE, MESSAGE and REMIND allow for structural shifts, models that are based on 'constant elasticity of substitution' (CES) functions, for example WITCH, have a tendency to remain close to the technology mix of the calibration period in case substitution elasticity is assumed low but can also yield substantial shifts if the substitution elasticity is high enough. Models like POLES which use technology readiness premiums can impede fundamental structural shifts by creating a differential between VRE and conventional technologies at the disadvantage of VRE due to the premiums (Pietzcker et al., 2017).

Constraints on certain technologies may also be motivated by **normative choices or by limited technical maturity and risk aversion.** Restricting the use of certain technologies, e.g. nuclear or CCS, may be imposed to reflect public resistance or sustainability limits for BECCS or biomass, up to excluding certain technologies.

Assumptions on technology costs and future price developments are typically not very transparent. A recent study by Krey and co-authors makes the effort to "look under the hood"[254] of for a range of large mitigation cost models and compile the underlying assumptions on techno-economic parameters including different cost parameters[255] (Krey et al., 2019). To improve transparency and comparability, Krey et al. moreover call for making the underlying values more transparent in future research and even building up a common database for techno-economic assumptions.

17.4.7.1.2 Implications for mitigation costs and discussion

Modellers typically have large discretion on how they implement techno-economic assumptions. The literature identifies **technology availability** e.g. in form of restrictions on the use of certain key technologies (e.g. nuclear or CCS to reflect public resistance or sustainability limits for BECCS or biomass) as a key driver for mitigation costs. Generally, the exclusion (or non-inclusion) of technology options increases mitigation costs (if those would have been cost competitive), as it reduces flexibility. Restricting technologies like BECCS, biomass and nuclear

[253] All three have cost mark-ups for curtailment, AIM/CGE also for storage costs, IMAGE features generalized back up costs (Pietzcker et al., 2017).
[254] Which is also the title of the study.
[255] The supplementary material of Krey et al. (2019) provides a comprehensive excel sheet for the collected parameters.

have been found to strongly impact costs and cost dynamics, also in national models (see e.g. for the UK (Kesicki, 2013)) or the EU (Capros et al., 2014b)).

The exclusion or restriction of negative emission technologies (NETs) has implications for the **intertemporal distribution of efforts** as lower near-term efforts cannot be compensated by negative emissions in the second half of the century, increasing near-term mitigation costs. Emmerling et al. (2019) moreover discuss the interplay of technology restriction and discount rates (Emmerling et al., 2019) (see Section 17.4.4 on discounting).

Constraints may also limit the **speed of phasing out conventional (carbon intensive) technologies**, e. g. assuming system inertia, or **scaling up new (low carbon) technologies**, or imposing restrictions on the energy mix to proxy system stability concerns. Partly, this may also be a result of assumptions on technological change and technology cost developments. Models including higher technological details (e.g. due to focusing on certain regions or on the energy sector only) can model the types of constraints more realistically. While the starting point of these assumptions may be of a descriptive nature, the implications for the results can be policy-prescriptive. Global models have typically underestimated the growth rate of low carbon technologies compared to what can be empirically observed, suggesting the need for a later phase out of fossils and resulting in a higher need for CCS or negative emission technologies. More favorable assumptions for RE diffusion typically decrease mitigation costs, especially in combination with endogenous technological change and learning by doing.

Several studies have moreover assessed how the **combination of techno-economic assumptions,** such as availability of low-carbon mitigation options as well as possibility for premature retirement of existing fossil-fuel based capital stock and ramp-up of low-carbon technologies, affect model flexibility and mitigation costs. For instance, the study conducted by Bertram et al. (2015) as a multi-model comparison study explores how policies imposed in the short-term impact long-term transformation pathways. A subset of models including MESSAGE-IAM, REMIND, and GCAM are rich in terms of availability of a broad range of low-carbon energy supply options and technologies. These models largely depend on net negative emissions in the second half of the century that causes overshooting the target prior to 2100. These models are thus characterized by comparably modest carbon prices. Models like MERGE-ETL, WITCH and POLES on the other hand, find higher carbon prices. This model reaction reflects the restricted mitigation potential of the energy system. For instance, in MERGE-ETL no early retirement of built capacities is allowed in the electricity sector, which is compensated by applying net negative emissions throughout the latter half of the century. By contrast, POLES and WITCH cannot achieve large net negative emissions in the long-term, they therefore need to steeply decrease emissions in the first half of the century with higher carbon prices.

The literature finds that WITCH reports much higher costs compared to GCAM. The latter provides a high flexibility and low technology costs, thus resulting in relatively low mitigation costs. On the other hand, WITCH is less flexible with respect to decarbonization of the electricity sector due to constraints on grid integration of variable renewables as well as nuclear power (Bosetti et al., 2015).

The more relevant question is whether the assumed constraints serve well to **represent reality**. One of the core objectives on the ADVANCE project was to "develop[..] a new generation of advanced Integrated Assessment Models"[256]. The study by Pietzcker et al., conducted under the ADVANCE project, looked into model assumption of selected ADVANCE models and their assumptions on energy system representation; it identified progress (as part of the ADVANCE

[256] See e.g. project description on the ADVANCE website (ADVANCE Project, 2016) which can be accessed under http://www.fp7-advance.eu/

project) in energy system representation compared to pre-AR5 model versions[257] (Pietzcker et al., 2017). Moreover, Pietzcker et al. conducted a qualitative assessment, rating model assumptions for six models of the ADVANCE project from ”0” (least realistic) to “+++” (most realistic) for different indicators of energy system modelling (see Table 27).

[257] This refers to model versions as they have been used for the Fifth Assessment Report of the IPCC in 2014.

Table 27: Qualitative rating of representation of energy system features in ADVANCE models (Pietzcker et al., 2017)

	Investment dynamics						Power system operation				Temporal matching of VRE and demand		Storage			Grid		
Model	Investment into dispatch. technol. differentiated by loadband	Investment into VRE (incl. feedback on the system)	Expansion dynamics	Capital stock inertia & vintaging	Structural shift of generation capacity mix	Love of variety	Dispatch	Flexibility & Ramping	Capacity adequacy	Curtailment	Wind/Solar complementarity	Demand profile evolution	Short-term storage	Seasonal storage	Demand response (incl. electric vehicles & V2G)	General transmission & distribution grid	Grid expansion linked to VRE	Pooling effect from grid expansion
AIM/CGE	0	+	0	++	++	++	0	0	0	++	+	0	+	0	0	0	0	+
IMAGE	+++	++	0	+++	++	++	+++	+	++	++	++	0	++	0	0	+	+	+
MESSAGE	++	++	++	+++	++	+	+	++	++	++	++	+	++	+	0	0	0	+
POLES	+	+	0	+++	+	++	++	++	+	+	+	+	+	++	+	0	0	+
REMIND	+++	+++	++	+++	++	+	++	+	++	++	+++	0	++	+++	0	+	+	+
WITCH	+	+	+	++	+	+	+	+	+	+	+	0	+	0	+	+	+	0

VRE = variable Renewable Energy; V2G= vehicle to grid

Rating of representation in the model from “0” = least realistic to “+++” = most realistic

Source: (Pietzcker et al., 2017)

As can be seen in Table 27, no model in ADVANCE performs well in each rating for all different indicators for energy system modelling. Moreover, several indicators seem more challenging to represent realistically as the best rating is one '+' out of maximally three, although for other indicators several models are rated with '+++' implying that models make progress to realistically represent energy sector characteristics.

Categorising the rated ADVANCE models based on the energy system modelling indicators and the qualitative rating by Pietzcker et al. (2017) suggests that models with a more realistic representation tend to yield lower carbon prices in earlier years; for example, can be seen below for the case of representation of investment into variable Renewable Energy (see Figure 80), reflecting whether models represent feedback effects with existing VRE capacities (see also Section 17.4.7.1.1).

Differences in assumptions on **future technology costs** also play a vital role. Bosetti et al. (2015) evaluates the extent to which uncertainty about future technology costs in key energy technologies[258] translates into different outcomes for three models: WITCH, GCAM and MARKAL-US. Although different models imply different variations in baseline emissions, the predominance of nuclear energy cost is identified as the main source of variation across models in this study (Bosetti et al., 2015). In climate-constrained scenarios, and in particular scenarios aiming at a stringent target such as RCP 2.6, they stress the relevance, in addition to that of nuclear energy, of biofuels, as it represent the main source of decarbonisation of the transport sector. Additionally, bioenergy can be coupled with CCS to produce negative emissions. It has been argued that GE-type global models based on constant elasticity of substitution nested functions to mimic the energy sector (e.g. WITCH model) are found to be much less sensitive to cost and efficiency variations of technologies and in average emissions increase by the end of the century, even under the most optimistic assumption of technology costs (Bosetti et al., 2015).

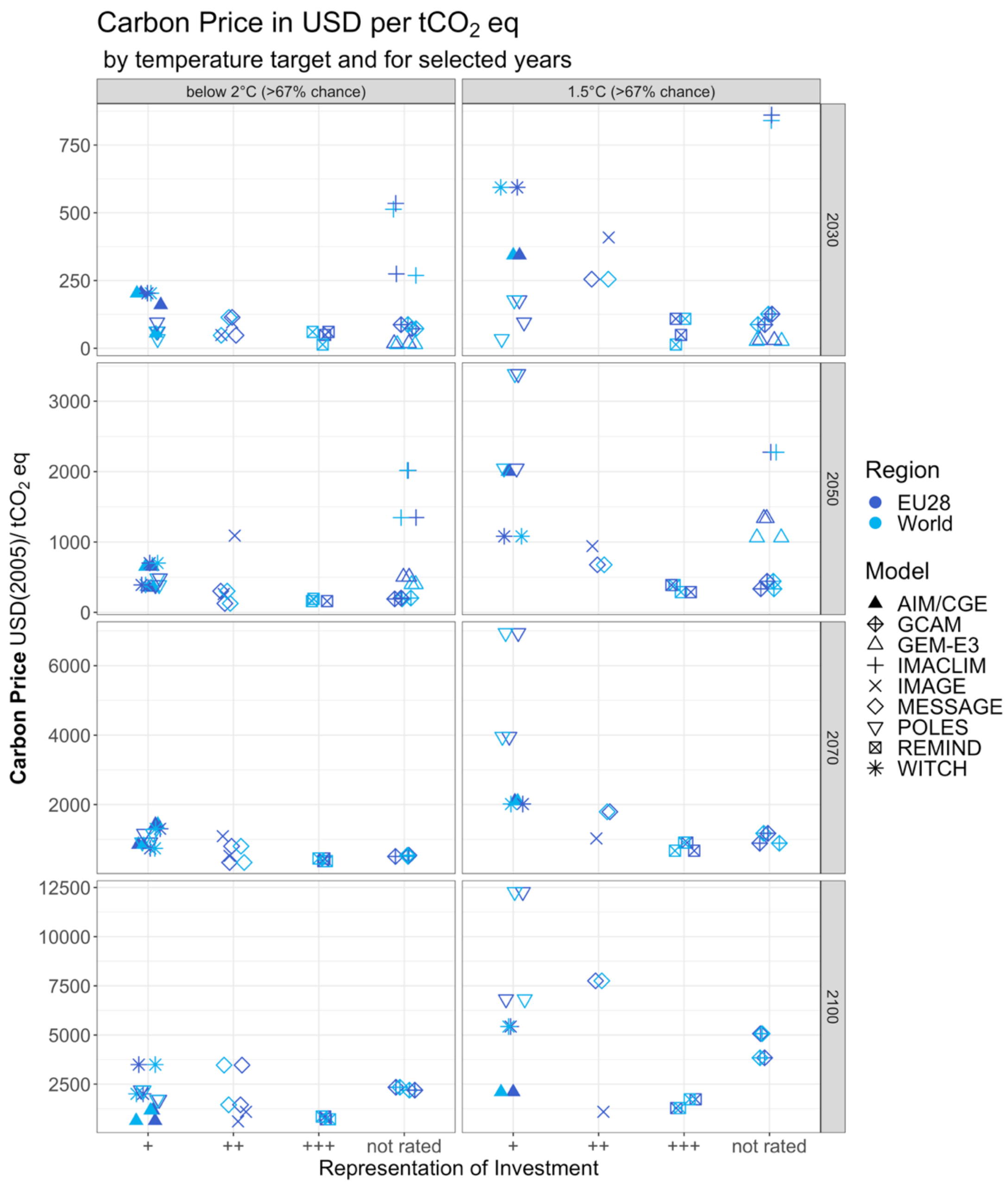
Here we illustrate such challenges by reviewing the treatment and performance of IAMs with respect to some of the rapidly changing technologies (e.g., solar, wind, and batteries). Our review shows that IAMs have difficulty in updating the cost of the rapidly changing technologies.

For technology costs, a core question is how well assumptions match reality. A recent review of global mitigation cost models finds that these models struggle to update their underlying cost assumptions for rapidly evolving technologies (Shiraki & Sugiyama, 2020). Figure 81 compares the technology cost assumptions for the global model CGAM with empirical data from IRENA and other sources. It shows that assumptions on levelised costs of electricity (LCOE)[259] for wind and solar in GCAM have been substantially higher than observed data would suggest.

[258] The technologies include liquid biofuels, electricity from biomass, CCS, nuclear, solar PV.

[259] LCOEs are a measure to compare the costs (over their entire lifetime) of different types of electricity generation technologies on a consistent basis.

Figure 80: Carbon Prices by Representation of investment into variable Renewable Energy (ADVANCE)

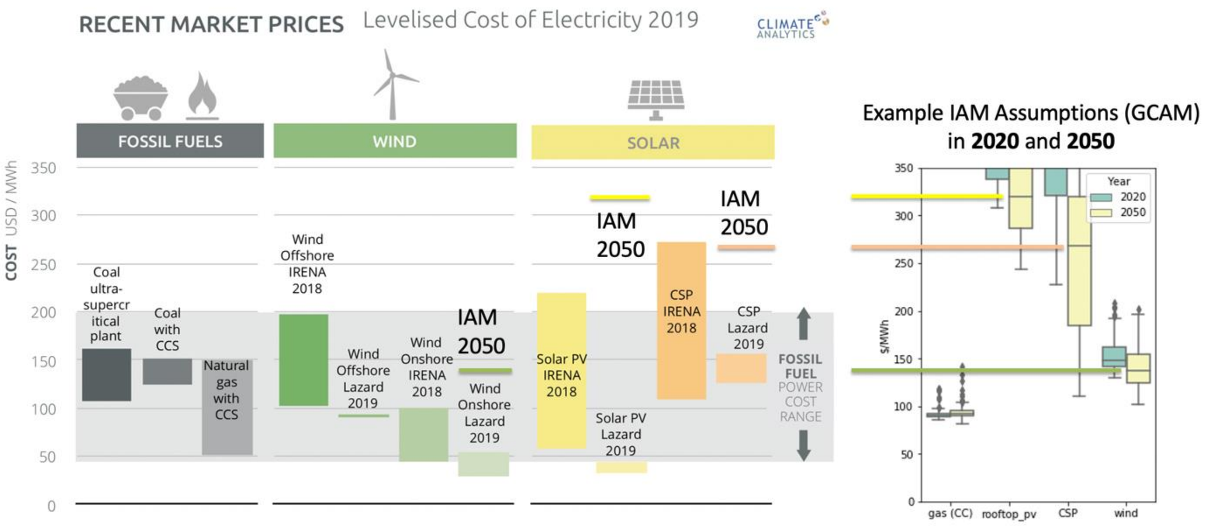


Note: The ratings represent a qualitative rating with "0" being least realistic and "+++" most realistic (from Pietzcker et al. 2017). Note differences in the y-scales to improve readability. MESSAGE=MESSAGE-GLOBIOM. Note that IMAGE assumes a ceiling value for the carbon price of 4000 USD/tC (1090.91 USD/tCO_2). Note that IMACLIM and GEM-E3 only report results until 2050. Note that not all models in ADVANCE have been rated by (Pietzcker et al., 2017). Note a potential selection bias for 1.5°C scenario results due to potential infeasibility issues to produce results for very ambitious scenarios. Note that POLES assumes substantially higher population growth (see Appendix Figure 113).
Source: own illustration, Climate Analytics based on ADVANCE database (IIASA Energy Program, 2019) and (Pietzcker et al., 2017) categorisation.

Part of technology costs are fuel costs. A sensitivity analysis assessing the key drivers for marginal abatement costs (MAC) for a partial equilibrium model focusing on the UK, does not find the MAC curve to be sensitive to different fossil fuel price development assumptions (Kesicki, 2013) (see Section 17.6). The study explains this with a number of counteracting factors such as higher fossil fuel prices decreasing the mitigation costs for renewable technologies, while they increase the costs for CCS being another key mitigation technology. Moreover, increasing carbon taxes overshadow the fuel price differences between scenarios.

Figure 81: Illustrative comparison of technology costs in a global model (GCAM) and observed technology costs

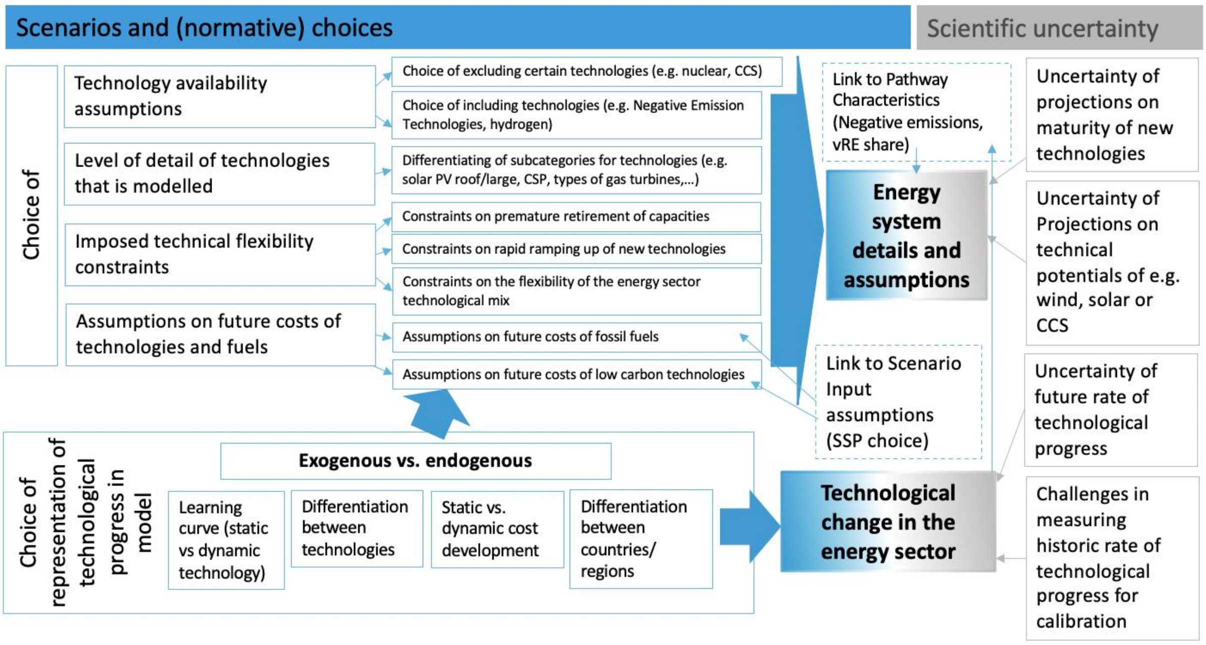
Levelised Cost of Electricity of different generation technologies in 2019



Source: own illustration, Climate Analytics based on data from LAZARD (2019) and IRENA (2019).

Figure 82 illustrates the (normative) choices and scientific uncertainties related to energy sector and technology assumptions. The topic of technological change is discussed in the following section.

Figure 82: (Normative) choices and scientific uncertainty related to assumptions concerning energy system representation and technological change



vRE = variable Renewable Energy; CSP= Concentrated Solar Power; CCS = Carbon Capture and Storage/Carbon Capture and Sequestration, SSP = Shared Socioeconomic Pathways

Source: own illustration, Climate Analytics.

17.4.7.2 Technological change in the Energy Sector

17.4.7.2.1 Heterogeneity in the literature and in ADVANCE

With respect to technological change, two main classes of models exist:

- models **lacking an explicit representation of technological change**, which take technology as an exogenously implied input factor disregarding the implications of policy measures and investment decisions on technological development.
- models with **endogenous technological change**, allowing for some portion of technological change to be influenced by deployment rates, market and policy incentives or investments in research and development (R&D).

For instance, the REMIND, IMAGE, and POLES models treat technological change endogenously. In REMIND, it operates under perfect foresight, the anticipation of benefits from technological learning results in an earlier and higher deployment of solar PV, despite temporarily higher LCOEs[260] (Luderer et al., 2014). Mercure and co-authors argue that models such "non-equilibrium models" (e. g E3ME) as they label them have a better representation of innovation and technological change compared to model types typically assuming markets to be in equilibrium such as CGE models and Optimal Growth models (Mercure et al., 2019).

Krey et al. (2019) compare techno-economic assumptions for fifteen global and national models. It differentiates between "static technology assumptions", i. e. technical characteristics that are assumed to not change over time, and "dynamic technology assumptions", i. e. conversion efficiency either assumed to remain constant or to vary over time. For costs, it differentiates between "static costs" and "dynamic costs", depending on whether capital and operation & maintenance costs of a technology vary over time or not. Based on this, Krey et al. (2019) group the projection strategies[261] of techno-economic parameters into four groups: (i) "static technology" with "static costs", (ii) "static technology" with "dynamic costs", (iii) "dynamic technology" with "static costs" and (iv) "dynamic technology" with "dynamic costs". While some IAMs adopt one of these four strategies for *all* technologies, others vary strategies for different technologies.[262]

Furthermore, techno-economic assumptions may also vary substantially between regions in some models. Using the example of gas power plants: while some global IAMs such as CAM_4.2 ADVANCE, GEM-E3, REMIND 1.6 and POLES MILES apply uniform techno-economic assumptions across all regions for new power plants, other models such as MESSAGEix-GLOBIOM_1.0, IMAGE 3.0 and WITCH-GLOBIOM 4.4 exhibit regional differences in capital costs and conversion efficiency assumptions for gas power plants (Krey et al., 2019).

[260] LCOE= Levelized costs of electricity.

[261] I.e. whether the assumption of time-invariation or time-variation are applied for projecting the parameters development over time.

[262] Typically, models that assume "dynamic technology" with "static costs" for fossil fuel technologies , instead use "dynamic costs" for technologies such as wind turbines, solar PV or nuclear (Krey et al., 2019)

Technological change in the ADVANCE database

Despite the above-mentioned challenges of drawing lines, we grouped the models that are part of the ADVANCE database as follows:

- Models exhibiting some form of endogenous technological change in the energy sector: IMAGE, REMIND, POLES, IMACLIM, WITCH, AIM/CGE, GEM-E3
- Models lacking an explicit representation of endogenous technological change: MESSAGE-GLOBIOM, GCAM

17.4.7.2.2 Implications for mitigation costs and discussion

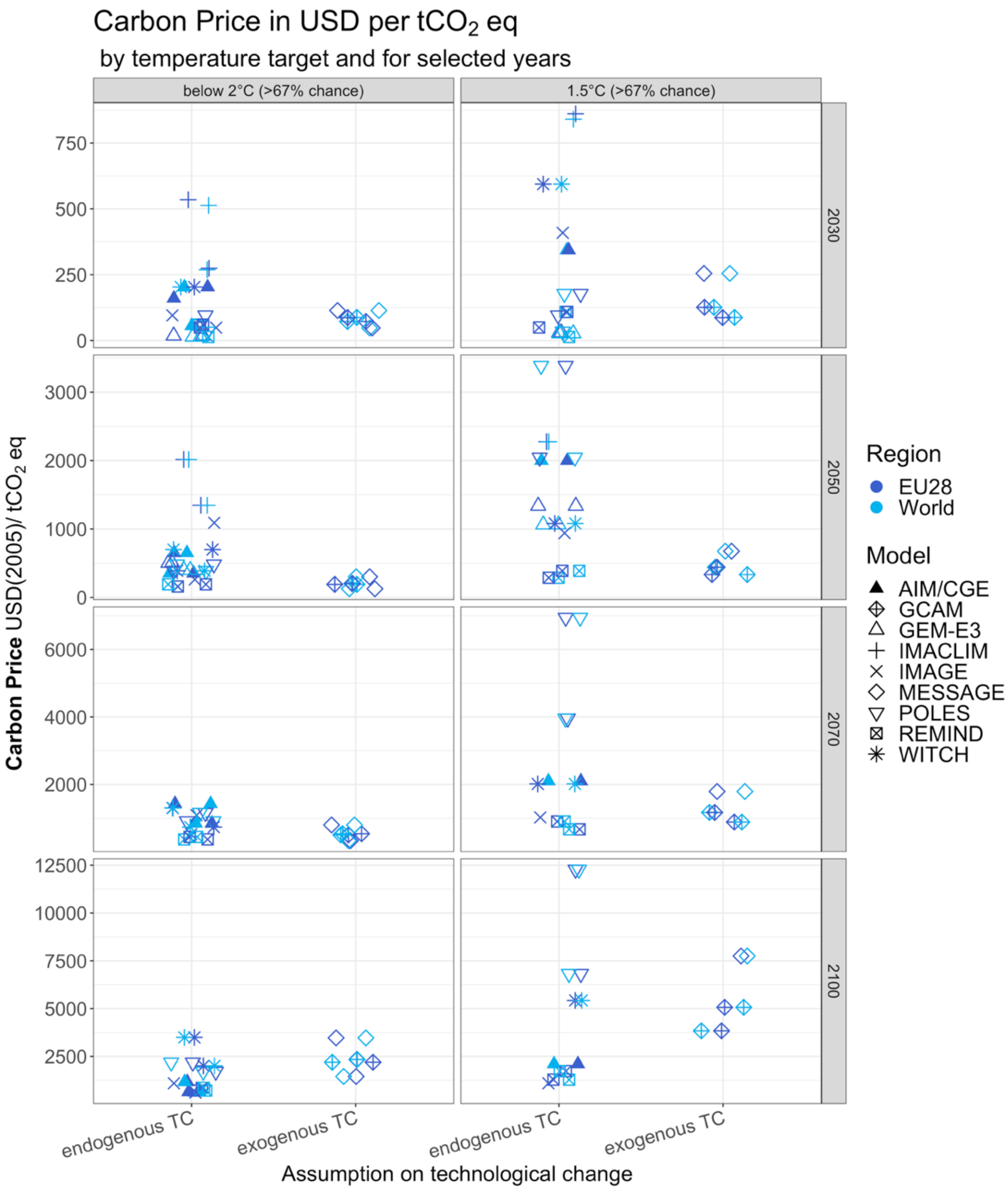
Technological change has implications for future costs of technologies, especially low carbon technologies and therefore for both, the least-cost energy mix as well as the overall mitigation costs. (Kuik, Brander and Tol 2009) argue that induced (i. e. endogenous) technological change can bring down costs for low-carbon technologies to the degree that the system locks itself in, mainly relying in these technologies as these have become least-cost options. In their meta-analysis, they find that induced technological change slightly increases marginal abatement costs in the short to medium term but tend to decrease for the long term[263] – as learning by doing is anticipated by a model, it might prefer to deploy low carbon technologies earlier to bring down the costs.

Models with exogenous technological change, which take technology as an exogenously implied input factor, disregard the implications of policy measures and investment decisions on technological development. Endogenous technological change represented via learning curves in a subset of bottom-up energy system models or IAMs (e.g. MARKAL, TIMES, REMIND, IMAGE, POLES) particularly impacts the investment costs of low-carbon technology options such as wind and solar, implying lower long-term costs for emerging technologies, in particular solar PV (see also Section 17.4.7 on energy system detail and Section 17.4.8.4 on vRE share). Intertemporal optimisation models, which assume perfect foresight supplemented with endogenous technological learning, tend to find lower aggregated mitigation costs compared to the models with no endogenous representation of technological change.

Comparing the carbon prices from the ADVANCE database by grouping models into how they represent technological change (Figure 83), suggests that ADVANCE models assuming exogenous technological change find slightly lower carbon prices than those assuming endogenous technological change, which contradicts the arguments provided above. Reasons for this may be that the carbon price is influenced by a combination of all factors explained in this chapter and other influencing factors may confound the picture as we do not have the possibility to directly compare the results from the same model making different assumptions on technological change. Moreover, models could in principle assume very high levels of exogenous technological change and thus a strongly decreasing trend in technology costs, leading to lower required carbon price levels.

[263] The coefficient for the long term (2050) shows the expected direction, however it is not statistically significant in (Kuik et al., 2009b).

Figure 83: Carbon Prices by differences in assumptions on technological change (ADVANCE)



Note differences in the y-scales to improve readability. MESSAGE=MESSAGE-GLOBIOM. Note that IMAGE assumes a ceiling value for the carbon price of 4000 USD/tC (1090.91 USD/tCO_2). Note that IMACLIM and GEM-E3 only report results until 2050. Note a potential selection bias for 1.5°C scenario results due to potential infeasibility issues to produce results for very ambitious scenarios. Note that POLES assumes substantially higher population growth (see Appendix Figure 113).
Source: own illustration, Climate Analytics based on ADVANCE database (IIASA Energy Program, 2019).

Figure 82 illustrates the (typical) choices with regard to energy sector and technology assumptions including technological change.

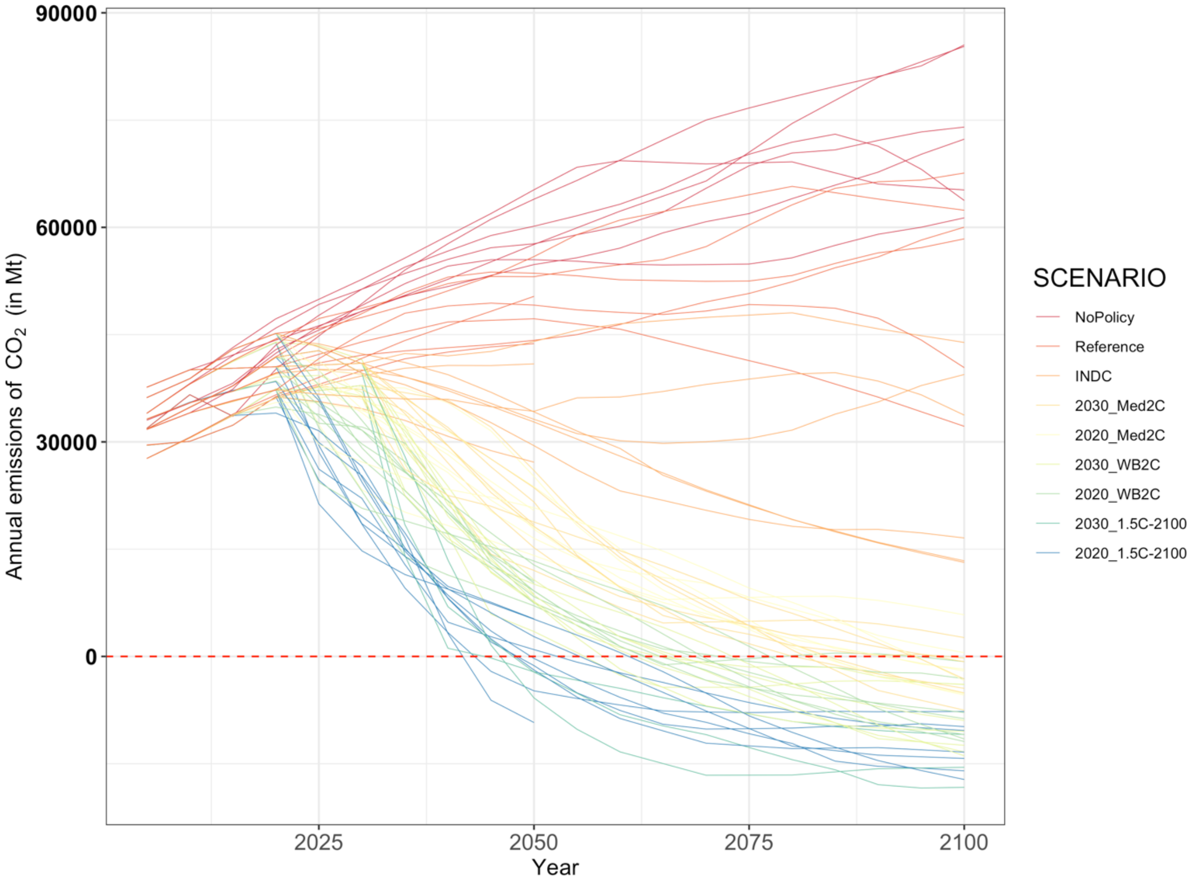
17.4.8 Pathways characteristics (resulting from underlying assumptions)

The categorisation of models based on core characteristics and model design is not always straight forward due to the high complexity and coupling of models. This section focuses on pathway characteristics that result from the underlying assumptions discussed above.

17.4.8.1 Emission pathways

Figure 84 shows the development of global CO2 emissions for all pathways available in the ADVANCE database, including weak climate policy scenarios[264]. For more ambitious scenarios (1.5°C and below 2°C (WB2C)) carbon emissions peak in the early 2020s and decline strongly after that, going to net negative carbon emissions even before mid-century for some 1.5°C scenarios. Figure 85 maps the carbon prices against the amount of global cumulative emissions (from 2016 onwards) at different points in time.

Figure 84: Emission trajectories for CO_2 (World) in the ADVANCE database

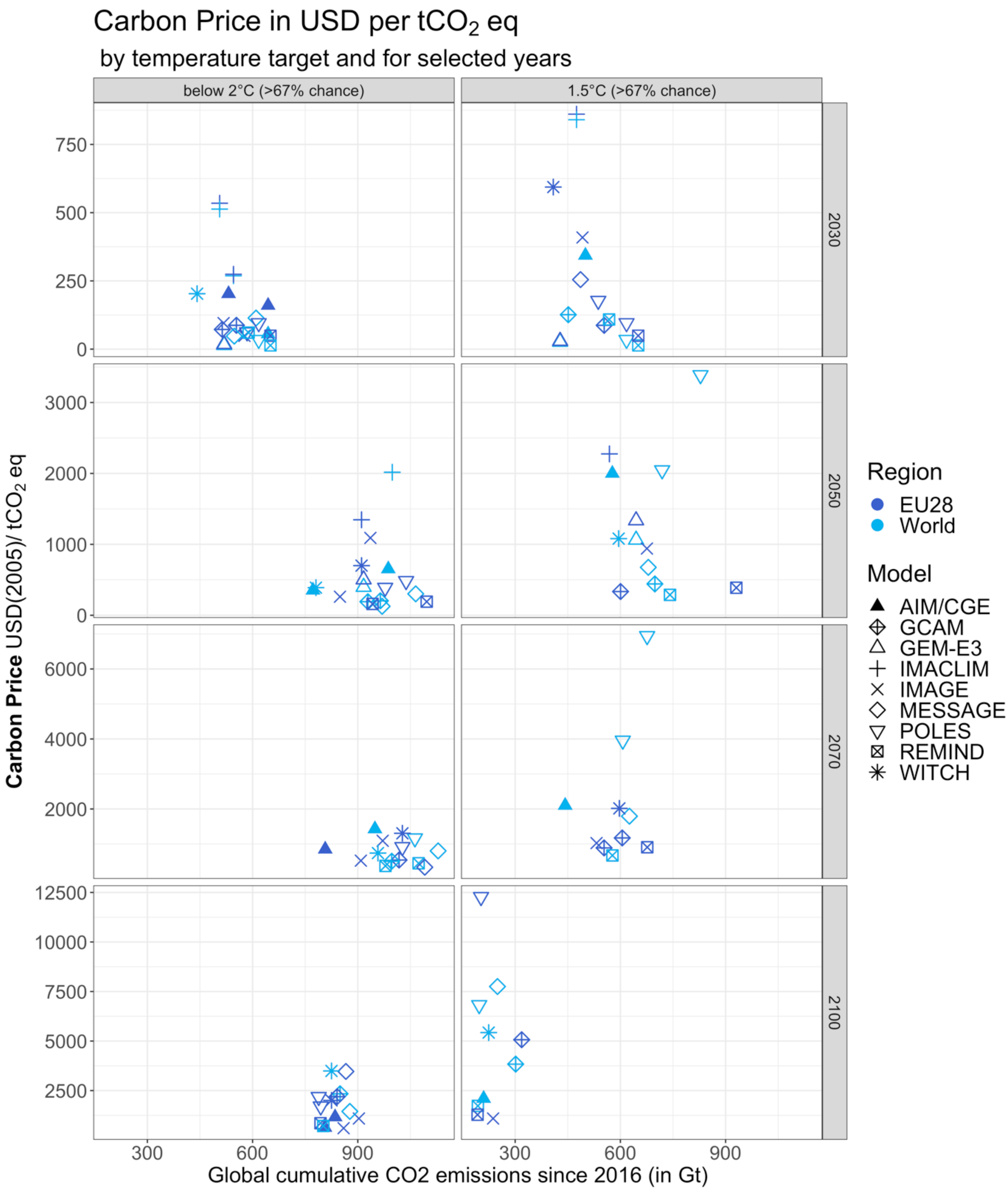


Global CO_2 emissions for the full set pathways in the ADVANCE database (excluding diagnostic scenarios). For a description of scenarios see Appendix

Source: own illustration, Climate Analytics based on ADVANCE database (IIASA Energy Program, 2019).

[264] These weak policy scenarios would result in warming above 2°C.

Figure 85: Carbon price by amount of global cumulative carbon emissions



Note differences in the y-scales to improve readability. MESSAGE=MESSAGE-GLOBIOM. Note that IMAGE assumes a ceiling value for the carbon price of 4000 USD/tC (1090.91 USD/tCO_2). Note that IMACLIM and GEM-E3 only report results until 2050. Note a potential selection bias for 1.5°C scenario results due to potential infeasibility issues to produce results for very ambitious scenarios. Note that POLES assumes substantially higher population growth (see Appendix Figure 113).
Source: own illustration, Climate Analytics based on ADVANCE database (IIASA Energy Program, 2019).

17.4.8.2 Deployment of Negative Emission Technologies (focus on BECCS)

Climate stabilization scenarios that aim at keeping global mean temperature rise within more ambitious limits rely on the use of technologies removing CO_2 from the atmosphere on a large scale (see e.g. Fuss et al. (2018), Minx et al. (2018), IPCC SR 1.5 (Rogelj, Shindell, et al., 2018), IPCC AR5 (Clarke et al. 2014; IPCC 2014)). In the literature, this is referred to as Carbon Dioxide Removal (CDR) or applying Negative Emission Technologies (NETs). A systematic review by Fuss and co-authors found that total NETs deployment across the 21st century is associated with a cumulative removal of carbon dioxide of 150–1,180 $GtCO_2$ (Fuss et al., 2018).[265] Partly based on the review by Fuss et al. (2018), the IPCC Special Report on 1.5°C confirmed that all pathways that limit global warming to 1.5°C with limited or no overshoot project the use of carbon dioxide removal (CDR) on the order of 100–1,000 $GtCO_2$ over the 21st century (SR1.5 (Rogelj, Shindell, et al., 2018)). For comparison, the carbon budget for 2016-2100 for the 1.5°C temperature limit in the ADVANCE project is around 200 $GtCO_2$.

There are several factors that contribute to this use of CDR by IAMs:

- Given that the remaining carbon budget for very ambitious mitigation targets is already almost exploited, large and fast cuts in emissions will be needed to still reach these targets.
- Model assumptions on the strength of inertia can hinder rapid shifts e. g. in the energy system, requiring steeper emissions cuts at a later stage to reach the same target
- Discounting of future costs - especially over long time horizons – leads to higher costs being shifted into the future, favoring NETs.
- Models tend to assume that demand is inflexible, and therefore underrepresent possible demand-side mitigation options, increasing the necessity for NETs to achieve stringent stabilisation targets.

Negative Emission Technologies identified in the scientific literature include reforestation and ecosystem restoration, afforestation, land management to increase and store carbon in soils, bioenergy production with carbon capture and storage (BECCS), enhanced weathering, and direct air capture of CO_2 (from ambient air) with CO_2 storage (DACCS). Ocean fertilization has also been discussed as a possible NET, although substantial doubt has been raised regarding its efficacy and possible adverse impacts on ocean ecosystems (Pörtner et al., 2019).

Models vary with regard to which Negative Emission Technology options are included. The majority of mitigation scenarios in CE-IAMs cover negative emissions generated from **bioenergy in combination with CCS (BECCS)**[266]**.** Several models or model versions have additionally included afforestation/reforestation, either by explicitly modelling the land use sector or by coupling to large-scale, geographically explicit land use models. For instance, GCAM and MESSAGE-IAM include the option to absorb atmospheric CO_2 by afforestation.

[265] Fuss et al. (2018) indicate that 1.5°C transition pathways make use of NETs in particular during the second half of the century, ranging between 1.3-29 $GtCO_2$ per year. By 2050, NETs deployment is already between 5 $GtCO_2$ per year and 15 $GtCO_2$ per year in most scenarios. The associated scale-up of NETs between 2030 and 2050 therefore takes place much more aggressively than in most 2°C scenarios, removing an additional 0.1–0.8 $GtCO_2$ every year on average. Also for the 2°C scenarios, while there are some scenarios available without net negative emissions at the end of the century, most scenarios feature considerable NETs deployment ranging from 5 $GtCO_2$ per year to 21$GtCO_2$ per year at the end of the 21st century (Fuss et al., 2018).

[266] The general principle of BECCS is as follows: Biomass is capturing CO_2 during plant growth and stores it in the form of organic material (e. g. trunks, roots). Then, the biomass is used to produce electricity (or another energy carriers) by e. g. burning it in a power plant producing electricity. Finally, CO_2 from that combustion process is captured and stored underground (CCS).

At the time of the Fifth Assessment Report and the Special Report on 1.5°C only a few published pathways have included Carbon Dioxide Removal (CDR) measures other than afforestation and BECCS, such as Direct Air Capture (IPCC SR1.5 2018).

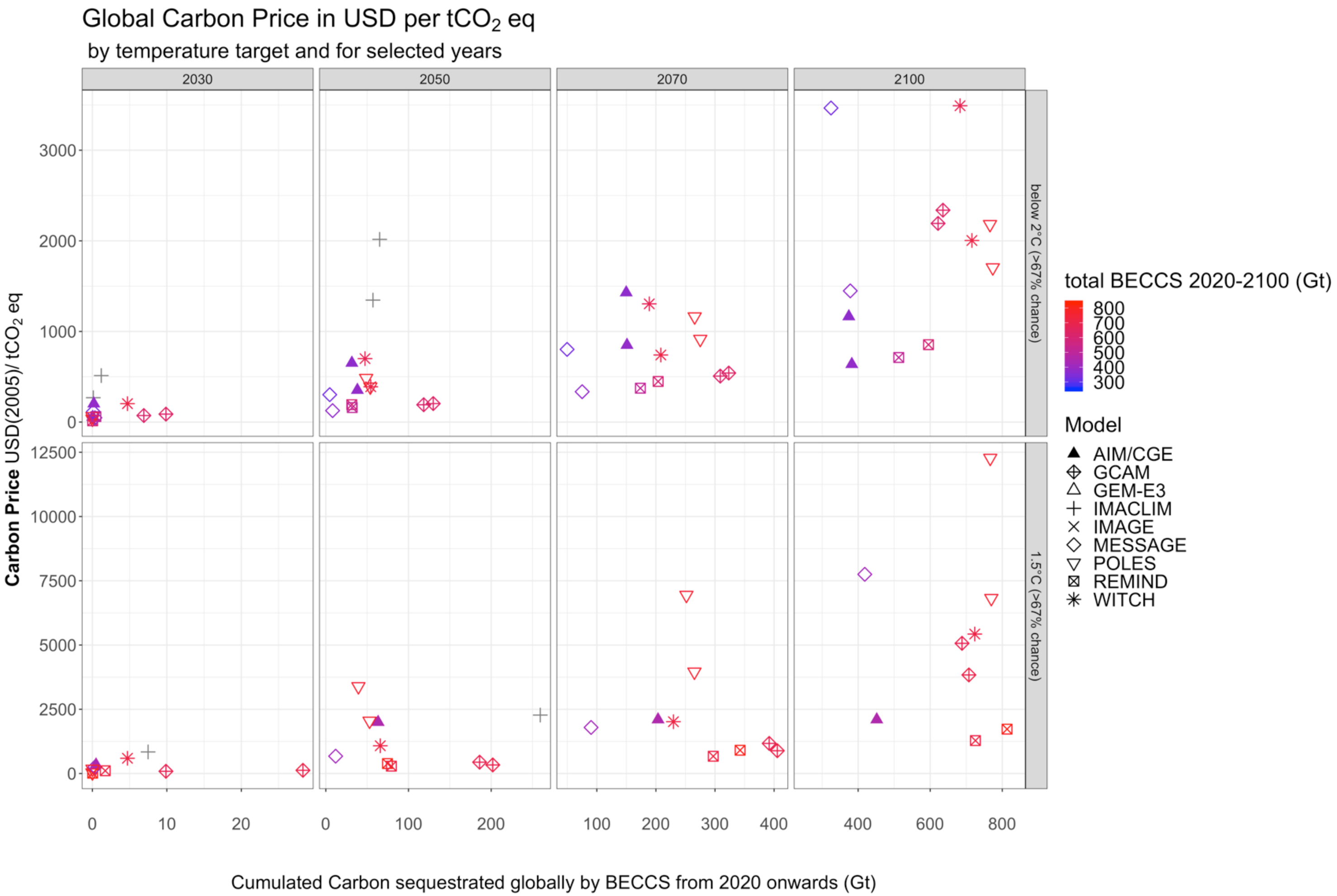
Recent studies suggest that Direct Air Capture (DAC) or DACCS (Direct Air Carbon Capture storage) could be more promising options than typically assumed in mitigation models (Breyer et al., 2019; Creutzig et al., 2019; Fasihi et al., 2019). While many mitigation cost models have had the tendency to assume relatively high cost for DAC, a recent study suggests that scaling up DAC deployment substantially could bring down costs to the point that it could become an affordable and cost competitive mitigation option, potentially bringing down costs to as below 50Euro/tCO_2 by 2040 (Fasihi et al., 2019). Also Creutzig and co-authors state that DACCS performs better than BECCS with regard to how much primary energy is required per ton of carbon sequestered, and DACCS would moreover require much less land than BECCS (Creutzig et al., 2019).

The availability of negative emission technologies (NETs) largely affects the model results in terms of long-term transformation of the energy system and the associated costs. At the time of the IPCC's Fifth Assessment report, many models have encountered very high costs or have run into feasibility issues for more ambitious scenarios (leading to about 450 ppm CO_2eq by 2100) without a negative emission 'backstop' technology, particularly when assumptions preclude or limit the use of BECCS (Edenhofer et al., 2014). Since then, scenarios have developed that find solutions without requiring large quantities of NETs for example by demand side mitigation (see Section 17.4.8.3). Köberle also argues that the role of BECCS could be reduced if other CDR technologies would be (better) represented in the models (Köberle, 2019). Moreover, Köberle argues that the omission of NETs other than BECCS, as well as certain model assumptions and structures (e.g. constraints in VRE integration, see Section 17.4.7 or end-use efficiency improvements), and especially the use of high discount rates (see Section 17.4.4) foster the role of BECCS in such models.

Models also vary in their imposed constraints to applying NETs with regard to i) assumed limits on the production of biomass, ii) assumed limits on the geological sequestration of carbon dioxide and iii) assumed constraints on the expansion of capital stock from period to period or the retirement of capital stock for NETS (see also Section 17.4.7 on energy system assumptions).

Figure 86 shows the cumulative amount of CO_2 sequestered by BECCS at different points in time over the century and the associated carbon price in the ADVANCE scenario database. It can be seen that 1.5°C pathways that rely more on BECCS tend to exhibit lower carbon prices in the first half of the century, which then strongly increase in the second half of the century. However, the spread of carbon prices in high BECCS scenarios in 2100 is large.

Figure 86: Global Carbon Price by cumulative BECCS (ADVANCE)



Total BECCS = Overall cumulative carbon sequestrated globally by BECCS from 2020 to 2100 (Gt). Note differences in the y-scales to improve readability. MESSAGE=MESSAGE-GLOBIOM. Note that IMAGE assumes a ceiling value for the carbon price of 4000 USD/tC (1090.91 USD/tCO_2). Note that IMACLIM and GEM-E3 only report results until 2050. Note a potential selection bias for 1.5°C scenario results due to potential infeasibility issues to produce results for very ambitious scenarios. Note that POLES assumes substantially higher population growth (see Appendix Figure 113).
Source: own illustration, Climate Analytics based on ADVANCE database (IIASA Energy Program, 2019).

The large-scale deployment of BECCS as the core negative emission technology assumed in most IAM scenarios needs to be scrutinized with regard to several factors:

- Technical feasibility of BECCS technology
- Scale of BECCS use assumed in the models
- Cost-related assumptions for BECCS
- Normative and ethical considerations

A crucial question is the general **technical feasibility of BECCS** and other NETs relying on carbon capture and storage (e.g. DACCS). As the BECCS technology combines two technologies – bioenergy and Carbon Capture and Storage (CCS) – the technical viability of both technologies would be a critical prerequisite for BECCS use. A recent report by the European Academies' Science Advisory Council (EASAC) finds that, while growing biomass can be considered a 'technology' that has been successfully tested and applied already, it is associated with very high energy use across the biomass supply and processing chain. Even if all flue gasses were to be captured, BECCS would still release a significant proportion of the carbon captured in crop growth (EASAC, 2018). Moreover, the CCS technology has not yet achieved 'off-the-shelf' technology status, despite playing a crucial role for many technologies in IAMs beyond BECCS (e.g. coal+CCS, gas+CCS, DACCS). While some sources consider CCS a 'proven technology' which has been in operation for decades[267], the EASAC stresses that technical issues remain and viable business models for CCS need to be developed.[268] The EASAC report moreover notes that CCS plans and investments in research in Europe have mainly been shelved and experience in CCS, that is currently being gained globally, mainly happens outside of Europe. Additionally, there have been public concerns against CCS with regard to the safety and environmental issues, although combining CCS with bioenergy rather than fossil fuel production might improve public acceptance (Nemet et al 2018, Wallquist et al 2012). Overall, the EASAC Report concludes that, while several BECCS demonstration projects already exist, these are mainly small scale BECCS projects and the technology is not yet a mature 'off-the shelf' technology. While NETs such as BECCS play a key role in the second half of the century, there is a strong near-term urgency to develop these technologies to be ready for wide-scale adoption as the period for their introduction and upscaling would already be between 2030 and 2050 (Minx et al., 2018).

A second crucial question is whether the anticipated **scale of BECCS use** that results from the model pathways can be considered realistic. The European Academies' Science Advisory Council (EASAC) concludes that NETs only offer limited realistic potential to remove CO_2 from the atmosphere and that the scale that can be found in some mitigation scenarios in the literature (finding as much as several gigatonnes of carbon each year post-2050 to be removed by CDR) does not seem in line with reality (EASAC, 2018). The envisaged large- scale employment of BECCS for removing gigatons from the atmosphere would require extremely large land areas for bioenergy, potentially competing for land with food production, ecosystem conservation and other land-based NETs. Estimates on land requirements range from around 1 to 1.7 hectares for

[267] See e.g the report from the European Commission (European Commission, 2019) (access under https://ec.europa.eu/info/sites/info/files/iogp_-_report_-_ccs_ccu.pdf)

[268] While the technology for extracting CO_2 from oil or natural gas fields (e. g. in Norway) is well established, the technology of separating it from power stations is still only tested at a relatively small scale (of the order of 1 million tonnes/year Carbon Dioxide Removal) and is still in demonstration or early commercialisation stages (EASAC, 2018). Moreover, the challenge of permanently and safely storing carbon in the ground (without leakage) remains. Storage sites that are considered 'save' for CCS may require long transportation from the site of emitting emissions to storage site, which again potentially produces emissions and increases the risk of leakage during transport (EASAC Report 2018). Economic incentives for (private) investments are missing and viable business models need to be developed to spur the required investments.

each tonne of carbon equivalent removed every year for forest residues, around 0.6 hectares for agricultural residues, and 0.1 to 0.4 hectares when purpose-grown energy crops are used (EASAC, 2018). Water and nutrient requirements of large-scale deployment are also likely to be challenging (Smith et al., 2016). Taking sustainability concerns into account, a systematic review of the literature by Fuss et al. (2018) finds that the best estimates for sustainable global BECCS potential in 2050 is 0.5–5 $GtCO_2$ per year (Fuss et al., 2018).

Another question is whether the **cost-related assumptions** in the models can be considered realistic. Models that conduct intertemporal optimization with perfect foresight assume perfect knowledge of the costs for BECCS and other NETs (if part of the model) for 20 or more year from now. BECCs (or even CCS itself) cannot yet be considered a mature 'off-the shelf' technology, and with large uncertainties in actual costs, technical feasibility and limits in scale, this assumption can be viewed very critically. Cost estimates for BECCS in the literature vary widely, ranging between 15US/tCO_2 and 400USD/tCO_2 (Minx et al., 2018). In view of the envisaged large-scale employment of BECCS and the resulting competition for land with possible trade-offs with agriculture and food production, the prices for biomass are uncertain and could potentially be high. Technologies that are currently considered very costly – like DACCS – but that do not rely on bioenergy could eventually turn out to be less costly than BECCS.

Finally, a critical question is whether the reliance on BECCS and other negative emission technologies at scale is in line with **ethical considerations**. Minx et al. highlight the risk of moral hazard associated with model scenarios that allow the large-scale deployment of NETs: while such deployment in cost-optimizing scenarios decreases the costs of long-term mitigation, reliance on CDR at large-scale tends to shift mitigation to later in the century, weakening near-term emission reductions, allowing warming levels to overshoot 1.5°C, and placing a larger mitigation and adaptation burden on future generations (Minx et al., 2018). Allowing such a temporary overshoot may have irreversible consequences if thresholds for tipping points are passed, and may reduce the capacity of land-based NETs to sequester carbon, for example if climate change impacts exacerbate trade-offs between BECCS deployment and food and water security, or if the carbon stored in forests and other ecosystems is released by forest fires or storm damage. Limitations on the speed, scale, and societal acceptability of NETs use determine the ability to return to below 1.5°C after an overshoot (Masson-Delmotte et al. 2018)), and there is remaining uncertainty about the effectiveness of net negative emissions to reduce temperatures after they peak, as we still have a limited understanding of the complexity of the carbon cycle and climate system (Masson-Delmotte et al. 2018).

Scenario design and model assumptions have important implications for intergenerational equity. For example, the discounting of future (potentially high) costs for NETs at higher rates leads to greater reliance on CDR later in the century and increases the carbon budget overshoot (Emmerling et al., 2019), elevating the risk of more severe climate damages (which are not captured in CE-IAMs). Similarly, scenarios are often designed to meet climate goals in 2100, allowing them to reach higher mid-century peak warming levels and subsequently to use NETs to reverse some of the damage. In an alternative scenario framework proposed by Rogelj et al. (2019), scenarios are designed to cap peak warming at a specific level, and then either stabilize or reverse warming afterwards (Rogelj et al., 2019). Such a framework makes clear the need for urgent near-term emissions reductions in addition to the use of NETs, and could be used to design scenarios that explicitly incorporate intergenerational equity.

Other ethical considerations not adequately captured by model scenarios include questions of responsibility and equity in deploying CDR (Fyson et al. 2020, Pozo et al. 2020) and the risks of adverse effects on sustainable development and human rights (Minx et al. 2018). In view of the potential competition for land and conflicts with biodiversity, food security and water, models need to represent crucial global as well as region-specific constraints to identify and balance trade-offs. Fujimori and co-authors find that if climate mitigation policies were carelessly designed, this could increase the number of people at risk of hunger by about 160 million in the year 2050. They also find, that the costs of avoiding these adverse effects by having inclusive mitigation policies would be small and amount to about 0.18% of the global GDP in 2050 (Fujimori et al., 2019).

Technologies allowing the removal of CO_2 from the atmosphere should not be used as an excuse for weak near-term climate policy. Ambitious near term mitigation action could significantly decrease carbon dioxide removal requirements to keep the Paris climate targets within reach (Strefler et al. 2018, IPCC SR1.5, 2018). In contrast, a delay in climate policy implementation and weak near-term ambition increase the necessity of relying on NETs at a later stage. Future socio-economic developments are also projected to play a crucial role (see also Section 17.4.3). The dependence on NETs increases in scenarios characterized by high energy demand and a strong preference for using fossil fuels (SSP5) (see e.g. Bauer et al. (2017)). Optimistic storylines following a sustainability narrative (SSP1) can have substantially lower NETs requirements than in middle of the road scenarios (SSP2), indicating the importance of taking demand side mitigation options into account.

17.4.8.3 Demand side mitigation

Stabilising emissions in the 1.5-2°C range requires also substantial reductions of direct demand-side CO_2 emissions, including energy demand for transport, industry and buildings. Demand-side mitigation can for instance be achieved by reductions in consumers' demands for energy services and energy-intensive materials through both increase of technical efficiency complemented with behavioral factors and lifestyle changes, replacing combustible fuels by electricity as a final energy and decarbonisation of fuels. Given the rapid decarbonization of power supply, an accelerated electrification of end-uses becomes an increasingly attractive mitigation option (Luderer et al., 2018). However, CE-IAMs have been criticized for emphasising technological rather than social change (Anderson & Jewell, 2019) as they tend to assume that demand is inflexible and therefore underrepresent possible demand-side mitigation options, which increases the necessity for NETs to achieve stringent stabilisation targets.

More recently, the topic of **demand side mitigation** has received increasing attention, especially with regard to exploring no- or low-overshoot scenarios for 1.5°C pathways (Rogelj, Shindell, et al., 2018). The various alternative mitigation pathways explored by these recent studies provide some diversity in the available measures for complying with the Paris Agreement, beyond the more limited set of options previously included in former studies, developing so-called *low energy demand (LED)* scenarios. A study conducted by Grubler and co-authors, creates a scenario assuming that global final energy demand in 2050 could be limited to 245 EJ, i.e. 40% lower than today's levels (Grubler et al., 2018). This is significantly lower than the final energy demand range in comparable IAMs mitigation scenarios, ranging from 300 to 700 EJ/yr in 2050 (Rogelj et al. 2018). Such a transition would require a shift to a more digitized world, with more decentralization and more focus on service provision rather than ownership of single purpose goods. Also Kriegler and co-authors consider radical declines in energy demand, and find this to be the most effective way of limiting future emissions (Kriegler et al., 2018).[269] Van Vuuren and co-authors develop an energy efficiency scenario in which the best available technologies for reducing energy and material use are employed from 2025 onwards (van

[269] Kriegler et al.'s (2018) most extreme scenario sees demand dropping at rates of up to 7.7% per year after 2020, before slowing again by the end of the century, to reach levels in 2100 as low as half of current energy demand. This rate of decline is almost three times as fast as current improvements in energy intensity.

Vuuren et al., 2018). A sensitivity analysis on Marginal Abatement Cost (MAC) curves in an energy system model for the UK confirms, that assumptions on demand substantially shift the MAC curve (Kesicki, 2013).

While Grubler et al. (2018) claim that such a low energy demand scenario could enable temperature to be limited to 1.5°C *without the need for technological Carbon Dioxide Removal* (CDR), as sufficient CDR (168 $GtCO_2$) is achieved through afforestation or reforestation alone, both Kriegler et al. (2018) and van Vuuren et al. (2018) find that energy demand reductions alone are not sufficient to eliminate the need for technological CDR such as BECCS.

Assumptions on demand side mitigation also affect the mitigation costs. The IPCC Special Report on 1.5°C for instance states that the LED (low energy demand) scenarios are at the lower end of carbon price ranges (see Figure 61 in Section 17.4.3) and Rogelj and co-authors also find that the sustainability narrative (SSP1) exhibits lower carbon prices (Rogelj, Popp, et al., 2018) (see Figure 60 in Section 17.4.3).

Yet, the low energy demand scenarios are built on strong assumptions with regard to lifestyle changes, such as profound dietary changes and strong energy efficiency improvements. The (political and social) feasibility of these profound changes remain to be proven realistic.

If demand side emission reductions are achieved e. g. through policy instruments such as energy efficiency standards or e. g. raising taxes on meat to foster dietary changes, the carbon price would not reflect the costs of these mitigation measures and would thus likely underestimate the full mitigation costs.

17.4.8.4 Variable Renewable Energy share

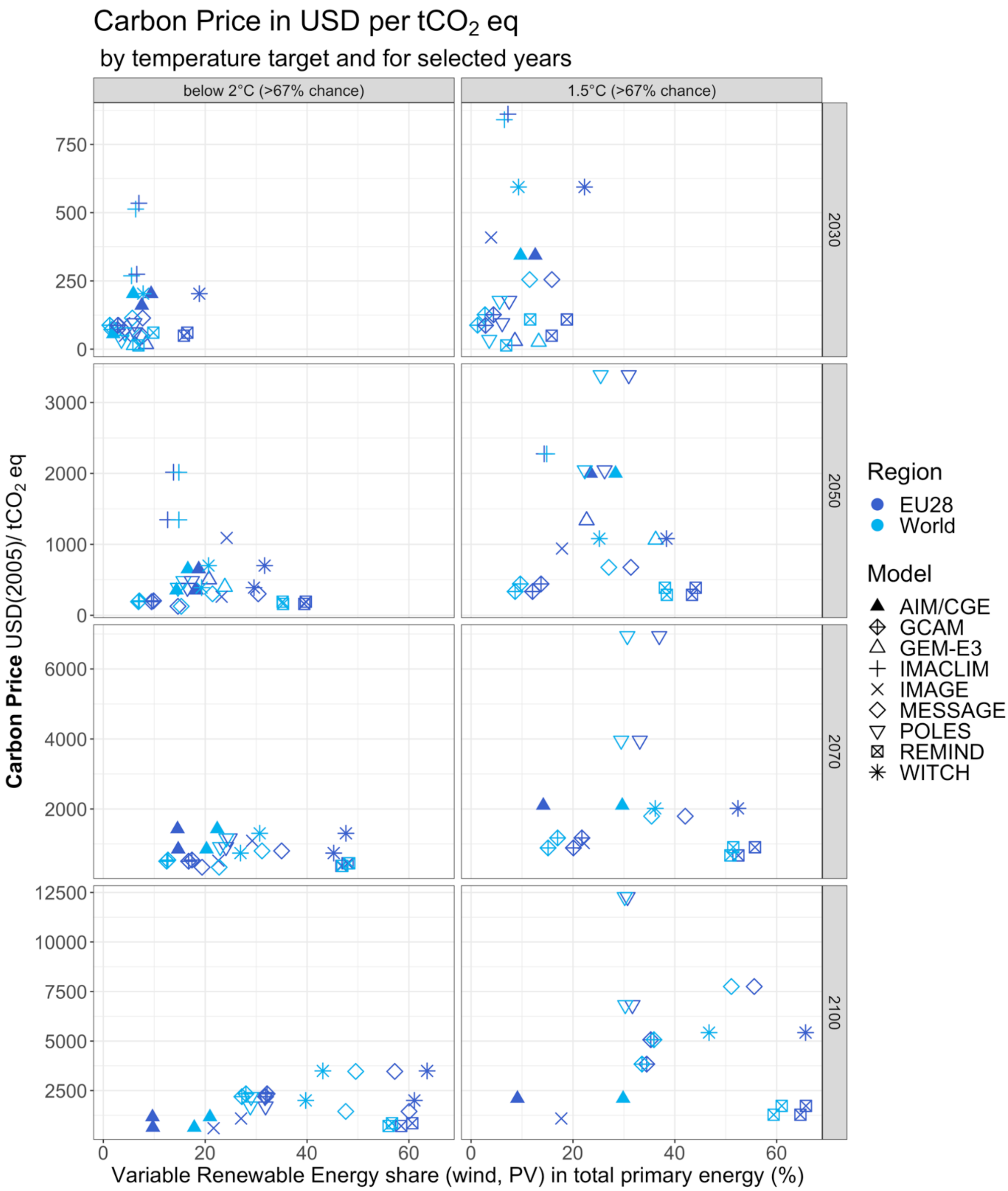
While the importance of BECCs has been highlighted in several IPCC reports, the strategical importance of solar PV has received less attention in global models (Creutzig et al., 2017). Historically, global models have consistently underestimated PV deployment (Creutzig et al., 2017; Pietzcker et al., 2017). Creutzig et al. (2017) attribute discrepancy between model-based PV estimates and actually observed development rates to three (partly interlinked) main factors: i) steep technological learning of PV, ii) policy support and iii) cost increases of competing technologies.

Comparing model results of the pre-AR5 model versions with the model versions improving their energy system representation under the ADVANCE project, Pietzcker et al. (2017) concludes that

- improving the power sector representation and the cost and resources of wind and solar substantially increased wind and solar shares across models.
- under a carbon price of 30$/$tCO_2$ in 2020 (increasing by 5% per year), the model-average cost-minimizing variable renewable energy share over the period 2050-2100 is 62% of electricity generation, 24%-points higher than with the old model version.

Figure 87 shows that the share of variable Renewable Energy in the energy mix in the ADVANCE database goes up to about 60% (in 2100) and ranges widely between models. It can be seen, that even in many 1.5°C pathways the vRE share in 2030 is below 20% and also in 2100 only reaches a maximum of around 60%. In recent years, research on 100% Renewable Energy Scenarios (largely based on country or regional case studies) has challenged these assumptions on slow RE penetration (for a review see Hansen, Breyer, and Lund (2019)). This confirms that global mitigation models tend to underestimate the deployment and growth of wind and solar compared to what is considered possible in other strands of literature.

Figure 87: Carbon price by share in variable Renewable Energy (ADVANCE)



Note differences in the y-scales to improve readability. MESSAGE=MESSAGE-GLOBIOM. Note that IMAGE assumes a ceiling value for the carbon price of 4000 USD/tC (1090.91 USD/tCO_2). Note that IMACLIM and GEM-E3 only report results until 2050. Note a potential selection bias for 1.5°C scenario results due to potential infeasibility issues to produce results for very ambitious scenarios. Note that POLES assumes substantially higher population growth (see Appendix Figure 113).
Source: own illustration, Climate Analytics based on ADVANCE database (IIASA Energy Program, 2019).

Models focusing on the EU or Germany confirm that Renewable Energy Deployment will play a key role (see Section 17.6 on national models). More importantly, studies with detailed energy system models find that high shares of RE of up to 100% in Europe (Connolly et al., 2016) or Germany (Hansen, Breyer, and Lund 2019, Hansen, Mathiesen, and Skov 2019) are technically feasible. Connolly and co-authors moreover find that while the costs for the RE-scenario is about

10-15% higher compared to a business-as-usual scenario, it would create about 10 million additional direct jobs due to shifting from imported fuels to local investments (Connolly et al., 2016). Power-to-Gas (i.e. producing either hydrogen or methane from - ideally renewable energy based - electricity) has recently been brought forward as a technology that could grow in relevance towards a sustainable energy transition (Lewandowska-Bernat & Desideri, 2018).

The need to improve the system integration and representation of vRE has been meanwhile identified by modellers. Ringkjob and co-authors provide an overview in modelling tools that have made efforts to better represent the integration of large shares of variable renewable energy, identifying and reviewing 75 models in total (Ringkjøb et al., 2018).

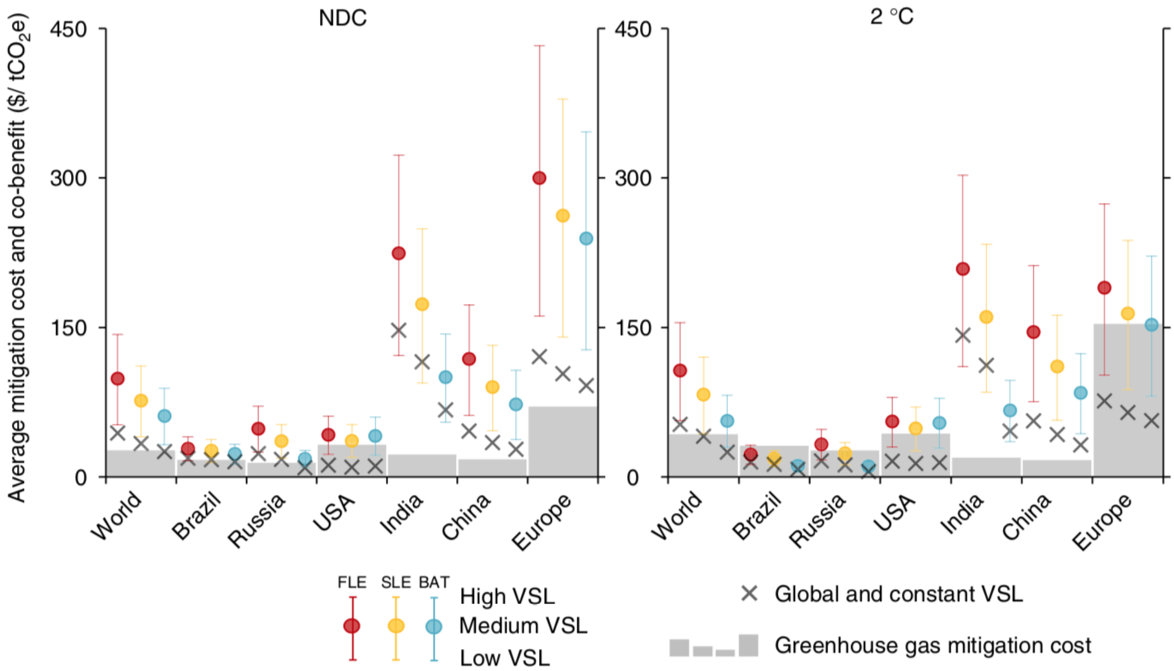
17.4.9 Accounting for Co-benefits

The majority of studies and models does not take possible co-benefits, i.e. positive and negative side effects of climate change mitigation measures, into account. More recently, modelers have started to explicitly account for selected co-benefits in their models, for example by linking their models with air quality models such as GAINS (Dong et al., 2015) or TM5-FASST (Markandya et al., 2018; Vandyck et al., 2018).

Co-benefits that have been frequently assessed are health benefits from reduced air pollution (energy sector and transport). Also assessed have been energy security benefits, and dietary changes/healthier lifestyles as well as impacts on agricultural yields. Savings from reduced fossil fuel import bills are also assessed (Capros et al., 2014b; European Commission, 2018a). Moreover, employment impacts (job creation) have been assessed, especially with regard to renewable energy technologies (Connolly et al., 2016). Impacts on competitiveness have also been assessed (Martin et al., 2016) as well as impacts for innovation (Calel & Dechezleprêtre, 2014), though often more in a short- to medium-term context.

Studies that account for co-benefits typically **find substantial benefits of mitigation policy that could at least partly outweigh (average) mitigation costs.** A recent study assessing air quality co-benefits for NDC and 2°C-consistent pathways find that co-benefits in form of reduced premature deaths and lost working days due to illness as well as improved agricultural productivity could more than offset climate change mitigation costs on a global scale in the majority of scenario settings (period 2015–2050) (Vandyck et al., 2018). Figure 88 shows that also for Europe the estimated health co-benefits can be large compared to the mitigation costs, even accounting for different normative assumptions on valorization of health (value of statistics life (VSL)) and without taking health impacts from climate damages into account (Vandyck et al., 2018). Coupling GCAM and the air quality model TM5-FASST another recent study also finds that health co-benefits considerably outweigh the mitigation costs for all the scenarios analysed (Markandya et al., 2018). In some scenarios, the median co-benefits were two times the median mitigation costs on a global scale. At the regional level, the share of mitigation costs that could be covered by health co-benefits for the European Union varied considerably, lying between 7% and 84%. In regions like China and India, health co-benefits alone would be sufficient to cover mitigation costs, while these regions could even see higher net benefits when striving for 1.5°C than for the less ambitious 2°C target. A review by Chang and co-authors finds that the majority of studies indicate substantial near-term co-benefits potential in terms of health benefits from e.g. reduced air pollution and dietary changes (Chang et al., 2017).

Figure 88: Mitigation costs excluding co-benefits (grey) and value of co-benefits from improved air quality due to climate policies comparing an NDC scenario and a 2°C Scenario



The value of the co-benefits of improved air quality due to climate polices in NDC and 2 °C scenarios. Values represent the average over 2015–2050 for Fixed Legislation (FLE), Stringent Legislation (SLE), and Best Available Technologies (BAT) air quality policies. Co-benefits include the value of avoided premature mortality as well as the co-benefits on the labour and agricultural markets via avoided work days lost and improved crop yields, respectively. The whiskers indicate high, medium, and low value of statistical life (VSL), heterogeneous across regions and time depending on GDP per capita. The black cross indicates results with the value of statistical life of 1.5 million US$(2005) constant across regions and over time. The shaded area presents the costs (change in welfare expressed as equivalent variation) of climate change mitigation policy over 2015–2050 and does not consider any co-benefits, nor does it include direct benefits of avoided impacts of climate change. Both cost and co-benefits are expressed per tonne of greenhouse gas emissions reduced excluding land use (change) and forestry.

Source: Figure 6 from Vandyck et al. (2018).[270]

However, Chang and co-authors highlight that studies seem better suited to assess interactions between climate policy and health as well as the (rough) order of magnitude of the co-benefits instead of providing accurate estimates of health co-benefits (Chang et al., 2017). Comparing co-benefits to mitigation costs requires a monetarization of typically non-monetary costs and benefits, such as health impacts. How to value e.g. death or incidences of diseases or life years lost or assigning a statistical value of life is a normative question. Yet, other research and policy areas like the health sector face similar normative questions. Different valorisations highly impact the level of estimated co-benefits, as can be seen in Figure 88 showing estimates for different VSL ranges.

Moreover, studies focus on selected co-benefits and cannot account for all diverse possible (direct and indirect) negative and positive side effects of mitigation policies. Transparency about underlying assumptions as well as sensitivity analyses are thus recommended. Yet, the insight

[270] Open Access article allowing usage under the Creative Commons Attribution 4.0 International License http://creativecommons.org/licenses/by/4.0/. No changes to the figure or caption were made.

provided by studies accounting for co-benefits are highly policy relevant as they identify certain non-market costs and benefits that are mostly ignored in models focusing long-term mitigation costs.

17.4.10 Modelling Communities

The literature on mitigation cost assessment and especially with regard to long-term transformation pathways and global mitigation cost models is characterized by different (partly overlapping) modelling communities. These communities can be described based on two indicators:

- ***Interlinkages between authors*** – Co-authorship relations: Based on the co-authorship information in the reviewed literature, it can be seen that authors related to different models have frequently cooperated in the form of common publications, with several key authors sticking out as particularly well connected in the overall network, taking on a leading role in the modelling communities (see Appendix).
- ***Cooperation between models*** – Joint participation in multi-model studies, such as model inter-comparison projects (see box on 'model inter-comparison studies'): There exist a wide variety of multi-model comparison studies, applying several models to assess the long-term implications of climate policies (e.g. Kriegler et al. 2013; Kriegler et al. 2014; Kriegler et al. 2015; Luderer et al. 2016). Part of these Model Inter-comparison studies is that main assumptions, such as e.g. input scenarios assumptions and mitigation targets, are harmonized to make the results of different models as comparative as possible. Normative assumptions, such as a model's discount rate, can be among the assumptions harmonized in inter-comparison exercises. Multi-model assessments such as Model Inter-comparison projects have played a strong role in shaping the scientific debate on mitigation costs and pathways, improving comparability of results across models, providing insights on main cost drivers and contributing to improvements in modeling. While not all such Model Inter-comparison studies focus on assessing mitigation costs, the joint participation of models in the same multi-model study indicates a form of cooperation, knowledge exchange and coordination between participating models. The insights from larger Model Inter-comparison Exercises have been used intensely for the IPCC assessment reports (e.g. AR5 WG III Report or the IPCC Special Reports) reviewing and synthesizing the existing literature, thereby also shaping the consolidated knowledge of the scientific community as well as the public and political debate. Table 46 (Appendix) compiles which models participated in recent important Model Inter-comparison projects or other multi-model studies assessing long-term transformation pathways. It shows that several of these model inter-comparison projects brought together a large set of very diverse models. It also shows that several models stand out for having been part of many of these multi-model studies. Most notably, these are CGAM, IMAGE, MESSAGE, REMIND, WITCH as well as GEM-E3, AIM/CGE and POLES – partly in different versions or model-couplings of the respective models.

The community working on global mitigation cost models can be considered a fairly small scientific community with a selected number of core authors and models shaping the scientific debate, especially as part of the IPCC's Assessment Reports. It is challenging to assess the degree to which the modelling community has an impact on the mitigation cost estimates as a) the models that are part of this community are very diverse as assessed above and b) there is to our knowledge a lack of similarly strong scientific communities assessing long-term mitigation costs that the cost estimates could be compared to (e.g. model intercomparison exercises for regional or national level models).

Modellers working on national or regional models appear less organized as a modelling community. Model inter-comparisons on EU-level models or Germany-focused models seem scarce with the noticeable exception of the multi-model study for the EU (Capros et al., 2014b).

17.4.11 Other influencing factors

The heterogeneity of models goes beyond the above-mentioned main influencing factors. Below, we mention a range of additional factors in which model design can vary.

- **Representation of end-use sectors:**
  - Models differ also with respect to the representation of end-use sectors, i.e. buildings, transport, and industry and the level of detail various contributing sub-sectors and technologies are modeled. The models, for instance, include heterogenous assumptions about the mitigation options available on the demand-side such as use of electricity or hydrogen in transport. The models mostly do not explicitly model the physical demand of various end-use sectors. For instance, some models (e. g. POLES), relate the industrial energy demand directly to economic drivers based on historical relationships, while other models (i. e. DNE 21+, IMAGE, TIAM-UCL) relate the material demand to economic drivers. In contrast, AIM/CGE, DNE 21+, GCAM, IMAGE, POLES, and TIAM-UCL include disaggregated representation of the industry sector. However, most global models, model the non-metallics minerals sector as a whole. Only a few global models (e.g. DNE 21+ and IMAGE) model the cement industry in a more explicit way (Kermeli et al., 2016).
  - National or regional models are more likely to also represent and assess the roles of different end-use sectors. In a multi-model study for Europe, Capros et al. show that a successful transport electrification plays an important role for Europe's decarbonization strategy, finding substantially higher carbon prices in the scenario with limited transport electrification (Pantelis Capros et al. 2014b). The very steep increases in carbon prices found by GEM-E3 after 2030 that signals that there would be difficulties to compensate abatement resulting from transport electrification by other mitigation options. Yet, if end-use sectors are not modelled explicitly, models may not be able to represent challenges towards electrification or other ways of decarbonization of sectors apart from the power sector.
- **Representation of trade:** Models also differ with respect of the flexibility implied by different assumptions/settings for the trade of final goods and primary energy carriers across regions. Higher flexibility in terms of trade results in lower aggregated mitigation costs as the mitigation actions would then occur where it is least expensive. Mitigation costs

in form of GDP losses tend to be higher in fossil-fuel exporting countries, due to declining exports and revenues (Vrontisi et al., 2018).

- **Land-use:**
  - Models also differ in the representation of land-use as well as the sophistication of the model of earth system process such as the carbon cycle. Some models do not treat land use change and associated emissions endogenously. WITCH for example represents land-use by using the mean response functions from the land-use model Global Biosphere Management Model (GLOBIOM).[271] Others explicitly model the land-use sector. This can be done through an emulator (e.g., MESSAGE-GLOBIOM[272]) or soft-linking (e.g. REMIND-MAgPIE[273]) with a detail land-use model. Other model, for example GCAM[274], integrate a detailed representation of different land-use components into their larger model structure.
  - The choice of SSP and the underlying policy assumptions can also impact how the land-use sector is treated. SSP1 and SSP5 assume an effective coverage of land-use emissions (at the same level as the energy and industry sector are controlled), while SSP2 and SSP4 assume that the effective coverage of land-use emissions is only intermediate (i.e., that REDD[275] is limited but agricultural emissions are covered effectively). SSP3 assumes that the coverage of land-use emissions is very limited due to implementations failures and transaction costs being high (Riahi et al., 2017). Assuming limited possibilities to control emissions from land-use (for example due to limited options to implement effective emission pricing on land-use emissions) imply that a faster decarbonization of other sectors such as the energy sector are needed to compensate the limited mitigation contribution from land-use. This can imply the need for higher carbon prices in these other sectors to remain within the same temperature limit (Guivarch & Rogelj, 2017)
  - The representation of land-use as well as the assumptions on natural or political constraints (e.g., limited afforestation potential, rivalry with food crops or limited public acceptance of BECCS) can play an important role in defining limits to applying technologies based on bioenergy. This again can have strong implications for the scope Negative Emission Technologies, e.g., in the form of BECCS (see Section 17.4.8.2 on NETs).
- **Representation of climate system:** Models can be linked to different climate and carbon cycle models of varying complexity to translate emissions into atmospheric concentrations, radiative forcing and global mean temperature change (Meinshausen et al. 2011). Frequently used climate models for that purpose are MAGICC and FAIR. This can mean that the same

[271] (IAMC wiki, 2020) (therein see WITCH – land-use)

[272] (IAMC wiki, 2020) (therein see MESSAGE-GLOBIOM – land-use)

[273] (IAMC wiki, 2020) (therein see - REMIND – land-use)

[274] (IAMC wiki, 2020) (therein see GCAM – land-use)

[275] REDD stand for Reducing Emissions from Deforestation and forest Degradation.

temperature target (or atmospheric concentration level target) can be associated with different levels of 'allowed' emissions to stay within the defined limit, if CE-IAMs use different climate modules. If models however define a common carbon budget to be applied to their analysis, as done in ADVANCE, differences in underlying climate modules do not matter. However, the same carbon budget constraint can be associated with different temperature targets (or atmospheric concentration level target) using different climate modules.

- **Global Warming Potentials of non-CO_2 emissions:** Applying different Global Warming Potentials (GWP)[276] to translate non-CO_2 emissions into CO_2-equivalents can also have an impact on mitigation costs. While the impact on mitigation costs between using the 100-year GWP from the Second IPCC Assessment report and the Fourth Assessment Report have been found to be rather minimal (M. van den Berg et al., 2015), the time scale matters substantially: van den Berg and co-authors find that applying a 20 year or 500 year GWP to non-CO2 GHGs significantly changes emission reduction and costs in their model as CO_2 reductions are favored over non-CO_2 GHGs if the GWP time horizon is increased (M. van den Berg et al., 2015). They find that using a 500-year GWP increases mitigation costs by about 20%.

17.5 Overview on model characteristics and behaviour with regard to mitigation costs for global models in the ADVANCE model intercomparison project

As seen in Section 17.4, mitigation costs estimates vary substantially across models, while general tendencies can be identified for specific models. Vrontisi and co-authors for example find that IMACLIM and WITCH tend to exhibit the highest cost estimates, while GEM-E3-ICCS, AIM/CGE and REMIND usually lead to lower cost estimates (Vrontisi et al., 2018).

Luderer and co-authors moreover explain this by the specific combinations of assumptions on different model structures, technology representation and input assumptions (Luderer et al., 2018):

- The **AIM/CGE** model represents a high level of detail to capture technological change in the power sector. The share of power generation technologies is determined based on a function of generation cost assumptions using logit functions. It is CGE-based model assumes a limited substitutability of technologies. This results in a relatively high remaining share of fossil fuels with CCS, with significant residual emissions. Low carbon intensity of industrial non-electric fuels on the other hand is due to a high deployment of biomass as a substitute for coal in industrial processes. AIM/CGE also represents CCS for industrial processes. The model estimates comparably high carbon prices for the 1.5°C scenario. This can be explained as imperfect substitution of fossil-based energy inputs to macro-economic production results in steeply increasing marginal abatement costs and by the fact that overall BECCS potential is more limited than in other models.

[276] For a discussion on different GWP metrics see (Rogelj & Schleussner, 2019; Schleussner et al., 2019).

- The **MESSAGE** model results in rapid and deep reduction of electricity sector emissions. Rapid decarbonization of the energy system is made possible through the early retirement of fossil-based power plants as well as electricity storage technologies enabling a high penetration of renewables. This flexibility of the model and high variety of mitigation technologies in the model support the transition of energy system, leading to lower cost estimates/ carbon prices compared to models with restricted substitutability of technologies like AIM/CGE.
- The **POLES** model also yields very high CO_2 prices, exhibiting the highest carbon price estimates in the ADVANCE database from 2050 onwards. This traces back to the solution dynamics of the model. As a recursive dynamic model, investments are made with an imperfect knowledge of future carbon prices increases. For the most ambitious scenario, all cheaper options have already been used, resulting in high marginal abatement costs.
- The **REMIND** model also foresees a rapid and deep reduction of electricity sector emissions. In particular, the REMIND model results in a high share of wind and solar in power supply. The REMIND model includes endogenous technological learning, and has updated techno-economic parameterization to recent trends. REMIND also accounts for storage and grid expansion as options to facilitate integration of variable renewable power. Assumptions on yield improvements in line with historical trends as well as representation of a variety of biomass feedstocks (including grassy, lignocellulosic biomass with high yields) result in comparably optimistic bioenergy potentials. Both biomass and afforestation are considered as CDR options. The REMIND model finds that achieving a 1.5°C target is still feasible even in a delayed mitigation action scenario (Luderer et al., 2018). This can be explained by the comparably optimistic assumptions that are applied for most mitigation options such as growth of renewables, biomass supply, etc. However, mitigation costs increase disproportionally with increasing abatement.
- The **GCAM** model represents both BECCS and afforestation as CDR options, and does not apply constraints to their deployment. For GCAM, achieving the most ambitious mitigation target is still feasible even in case of a delay in action. This can be explained by GCAM assuming high CDR potential as well as relevant additional abatement potentials in residual CO_2 emissions from fossil fuel and industry to make up for the excess near-term emissions in the ambitious mitigation scenario with delayed action compared to the ambitious scenario with early action.
- In contrast most other models assuming perfectly functioning markets, **IMACLIM** is characterized by assumptions of imperfect foresight combined with market and institutional imperfections. This rather exceptional combination explains that, under a carbon tax, mitigation costs can result in GDP losses that are far more significant than in the case of assuming perfect foresight and existence of competitive markets (Kriegler, Petermann, et al., 2015). Also, in the ADVANCE database, the carbon prices of IMACLIM are among the highest across all models.

Table 28 provides an overview on the different model characteristics for ADVANCE models.

Table 28: Overview on model characteristics for ADVANCE models

	AIM/CGE	GCAM	GEM-E3	IMACLIM	IMAGE	MESSAGE-GLOBIOM	POLES	REMIND	WITCH
Model type	CGE model	PE model	CGE model	CGE model	Energy-Land PE model	Energy system GE growth model	Energy system PE model (econometric)	Energy system GE growth model	Energy system GE growth model
GHG coverage	Several GHGs	Several GHGs	Several GHGs	CO_2 only	Several GHGs	Several GHGs	Several GHGs	Several GHGs	Several GHGs
Time horizon	2100	2100	2050	2050	2100	2100	2100	2100	2100
Objective function	Max. welfare	Min. energy system costs	Max. welfare	Max. welfare	Min. energy system costs	Min. energy system costs	Min. energy system costs	Max. welfare	Max. welfare
Representation of economy	Detailed, multi-sector representation	Exo-genous para-meter	Detailed dynamic multi-sector representation	Detailed dynamic multi-sector representation	Exo-genous para-meter	Simpli-fied aggr. representation	Exo-genous para-meter	Simpli-fied aggr. representation	Simpli-fied aggr. representation
Foresight and solutions mechanism	myopic/ dynamic re-cursive	myopic/ dynamic re-cursive	myopic/ dynamic re-cursive	myopic/ dynamic re-cursive	myopic/ dynamic re-cursive	perfect foresight /inter-tem-poral optimisation	myopic/ dynamic re-cursive	perfect foresight /inter-tem-poral optimisation	perfect foresight /inter-tem-poral optimisation
Technological change (TC)	Some form of endo-genous TC	lacking an explicit represen-tation of endogenous TC	Some form of endo-genous TC	Some form of endo-genous TC	Some form of endo-genous TC	lacking an explicit representation of endogenous TC	Some form of endo-genous TC	Some form of endo-genous TC	Some form of endo-genous TC
Rating of energy system represen-tation*	”0”:10 ”+”:4 “++”:4 “+++”: 0	Not rated	Not rated	Not rated	”0”:4 ”+”:4 “++”:7 “+++”:3	”0”:3 ”+”:5 “++”:9 “+++”:1	”0”:3 ”+”:10 “++”:4 “+++”:1	”0”:2 ”+”:5 “++”:6 “+++”:5	”0”:3 ”+”:14 “++”:1 “+++”:0

* Using qualitative ratings based on Pietzcker et al. (2017). Pietzcker and co-authors rate a selection of models with regard to how realistically a set of in total 18 different energy system aspects are modelled, from least realistic (0) to most realistic (+++). The numbers stated in this table indicate how often the respective model has been assigned the respective qualitative grade.

17.6 EU- or Germany-focused mitigation cost analyses

Global mitigation cost models typically feature a globally uniform carbon price to reach a predefined temperature limit. Having a global scope, those models are not particularly useful in informing national mitigation policies. National or regional models are better suited for this.[277] National mitigation cost models are a tool to identify and analyse country-specific mitigation pathways. Compared to global models they consider national circumstances in more detail (e. g. pre-existing policies, existing industries, potential of renewables, technology costs, social acceptance and feasibility of certain technologies). They usually also take into account the international context, but in a rather rough way and as an exogenous influence. As input, national models cannot use a temperature limit, as the temperature increase depends mainly on the mitigation effort of other countries. Instead, they use national reduction targets (often –80% and –95% compared to the emission level in 1990).

Given the limitation of global models to reflect region- or country specific details, this section reviews selected studies focusing on the EU, Germany or other European countries.

17.6.1 Studies focusing on Europe

17.6.1.1 In-depth Analysis of the EU Commission in support of the EU long-term strategic vision “A clean planet for all”

17.6.1.1.1 Aim

End of November 2018, the European Commission (EC) has released its long-term strategic vision “A clean planet for all”[278] as well as an accompanying In-depth Analysis conducting a comprehensive impact assessment building the foundation of the strategic vision (European Commission, 2018a).[279] As an input to the EU’s contribution to the Paris Agreement, the objective of these documents is laying out a ‘vision’ for Europe transitioning to a climate neutral economy until 2050 – aiming for Europe’s net GHG emissions to be zero in 2050.

The In-depth Analysis of the EC is covering mitigation pathways for all relevant sectors and greenhouse gases (GHGs). Moreover, it conducts an impact assessment for a range of different economic and social implications, such as investment requirements, energy system costs and prices, fuel expenses (e. g. for households), net fossil fuel import benefits, employment impacts, impacts on competitiveness, air quality benefits and macro-economic impacts.

While the main part of the EC in-depth analysis looks into eight scenarios, the analysis of the macro-economic impacts in the EC’s in-depth analysis is a shorter ‘add-on’ analysis which differs from the main analyses: it uses a different modelling suit, it focuses on a subset of only two of the eight scenarios from the main analysis and it has different baseline scenario assumptions. This will be explained in more detail below.

[277] There is another reason to use national models. Global model demand higher mitigation efforts in developing countries, as it is globally more efficient to reduce emissions in those countries — at least in early phases. The reason is that the marginal costs in developing countries are lower. The ensuing equity concerns could in principle be dealt with international transfers. Yet, at the required scales those transfers are politically not feasible. It is thus not possible to separate efficiency and equity as demanded by text-book economics and therefore appropriate to define and model national mitigation goals and the respective mitigation costs (see e.g. also (Stiglitz et al., 2017)).

[278] (European Commission, 2018a): The Communication of the EC can be downloaded here.

[279] More information on the background process can be found in Chapter “Towards the climate policy of 1.5°C climate change” of Thomas Stoerck and Tom van Ierland (Thomas Stoerk & Tom van Ierland, 2019), download here

Note that in September 2020 a new impact assessment of the European Commission has been published[280]. This was however too late to still be included in the analysis for this report.

17.6.1.1.2 Approach

The EC in-depth analysis uses different modelling suites for the core chapters analysing the eight scenarios compared to the chapter focusing on the macro-economic impacts.

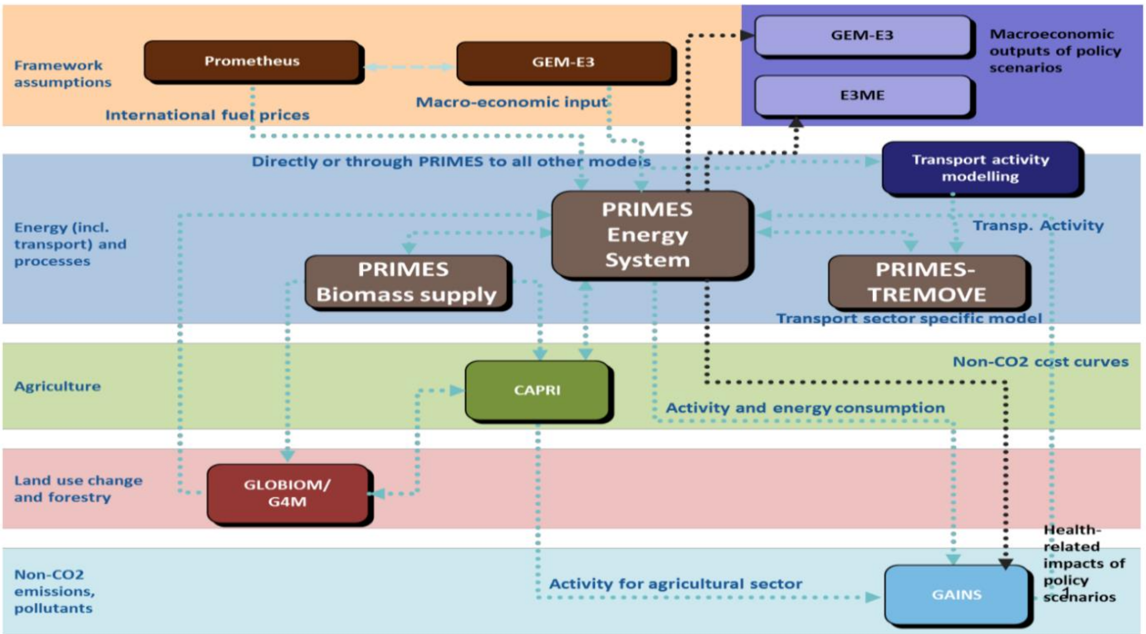
Main analysis

The main modelling suite has already been used by the EC in previous analysis, while improving it over time. It covers:

- The entire energy system (energy demand, supply, prices and investments)
- All GHG emissions and removals
- 1990 to 2070 time horizon (with 5 year timesteps)
- Comprising all individual EU member states as well as EU candidate countries (and where relevant Norway, Switzerland and Bosnia and Herzegovina)
- Impacts: on all energy sectors (PRIMES[281] and its satellite models on biomass and transport), agriculture (CAPRI), forestry and land use (GLOBIOM-G4M), atmospheric dispersion, health and ecosystems (acidification, eutrophication) (GAINS); macro-economy with multiple sectors, employment and social welfare (GEM-E3).

The models are linked with each other to ensure consistency of the scenario built up. Figure 89 shows the modelling suite and the interlinkages as an overview.

Figure 89: Modelling Suite and Model Interlinkages used by the European Commission's In-depth Analysis



Source: Appendix 7.2 of EC in-depth analysis (European Commission, 2018a)

[280](European Commission, 2020)

[281] The EC had commissioned a project called ASSET to critically review and update the technology and transport assumption of the PRIMES model in July 2018 (E3Modelling et al., 2018) , download under (https://ec.europa.eu/energy/sites/ener/files/documents/2018_06_27_technology_pathways_-_finalreportmain2.pdf)

Macro-economic impact analysis

The analysis of the macro-economic impacts in the EC's in-depth analysis is a shorter 'add-on' analysis for which the model suite differs from the main analyses. It was conducted using the following three **models** for this part of the analysis

- The CGE model JRC-GEM-E3[282] from the EU's Joint Research Center as main model, complemented by
- the macro-econometric model E3ME[283] from Cambridge Analytics and
- the macro-economic model QUEST[284] from the Directorate General Economic and Financial Affairs

17.6.1.1.3 Scenarios and core assumptions

Main analysis

The EC in-depth analysis is based on one baseline scenario and a set of eight mitigation scenarios exploring different views on mitigation options.

Table 29: Overview on Mitigation Scenarios and their characteristics

	Electrification (ELEC)	Hydrogen (H2)	Power-to-X (P2X)	Energy Efficiency (EE)	Circular Economy (CIRC)	Combination (COMBO)	1.5°C Technical (1.5TECH)	1.5°C Sustainable Lifestyles (1.5LIFE)
Main Drivers	Electrification in all sectors	Hydrogen in industry, transport and buildings	E-fuels in industry, transport and buildings	Pursuing deep energy efficiency in all sectors	Increased resource and material efficiency	Cost-efficient combination of options from 2°C scenarios	Based on COMBO with more BECCS, CCS	Based on COMBO and CIRC with lifestyle changes
GHG target in 2050	-80% GHG (excluding sinks) ["well below 2°C" ambition]					-90% GHG (incl. sinks)	-100% GHG (incl. sinks) ["1.5°C" ambition]	
Major Common Assumptions	• Higher energy efficiency post 2030 • Deployment of sustainable, advanced biofuels • Moderate circular economy measures • Digitilisation • Market coordination for infrastructure deployment • BECCS present only post-2050 in 2°C scenarios • Significant learning by doing for low carbon technologies • Significant improvements in the efficiency of the transport system.							
Power sector	Power is nearly decarbonised by 2050. Strong penetration of RES facilitated by system optimization (demand-side response, storage, interconnections, role of prosumers). Nuclear still plays a role in the power sector and CCS deployment faces limitations.							
Industry	Electrification of processes	Use of H2 in targeted applications	Use of e-gas in targeted applications	Reducing energy demand via Energy Efficiency	Higher recycling rates, material substitution, circular measures	Combination of most Cost-efficient options from "well below 2°C" scenarios with targeted application (excluding CIRC)	COMBO but stronger	CIRC+COMBO but stronger
Buildings	Increased deployment of heat pumps	Deployment of H2 for heating	Deployment of e-gas for heating	Increased renovation rates and depth	Sustainable buildings			CIRC+COMBO but stronger
Transport sector	Faster electrification for all transport modes	H2 deployment for HDVs and some for LDVs	E-fuels deployment for all modes	Increased modal shift	Mobility as a service			• CIRC+COMBO but stronger • Alternatives to air travel
Other Drivers		H2 in gas distribution grid	E-gas in gas distribution grid				Limited enhancement natural sink	• Dietary changes • Enhancement natural sink

Source: (European Commission, 2018a)

The **eight mitigation scenarios** (see Table 29) share the same assumptions until 2030 – assuming that the EU will meet its 2030 targets from the time of the analysis. Only after 2030, the eight mitigation scenarios differ in how they envision to achieve the mitigation and the level of ambition. Overall, the scenarios can be attributed to three different categories of ambition levels:

282 Find more information on this model on this website: https://ec.europa.eu/jrc/en/gem-e3/model

283 Find more information on this model on this website: https://www.camecon.com/how/e3me-model/

284 Find more information on this model on this website: https://ec.europa.eu/info/business-economy-euro/economic-and-fiscal-policy-coordination/economic-research/macroeconomic-models_en

- Scenario category I: Five scenarios envision to achieve about 80% reduction (85% with sinks included) compared to 1990 levels by 2050, each scenario having a different technology focus how to achieve this.
- Scenario category II: One scenario (a combination of four of the above scenarios) for reaching 90% reduction (incl. sinks).
- Scenario category III: Two additional scenarios building on selected previous scenarios reaching net carbon neutrality (including sinks)[285] by 2050 in different ways. In addition, there are two further variants of these, one assuming that biomass is limited (1.5LIFE-LB) and one scenario for industry (Mix95).

Note that only two of the eight main mitigation scenarios (labelled 1.5TECH and 1.5LIFE) aim to achieve net-zero GHG emissions by 2050 – which is the target defined in the underlying strategic vision. The 1.5TECH scenario assumes considerable use of negative emission technologies (BECCS and DACCS) to achieve carbon neutrality while the 1.5LIFE assumes that lifestyle changes and circular economy would allow for lower deployment of carbon removal technologies. Biofuels play a role in all scenarios – with possible trade-offs between biofuels and food security or land-use.

While the EC in-depth analysis (European Commission, 2018a) labels the five scenarios of category I as “contributing to Paris Agreement goal of well below 2°C” (page 316) , of category II as “aiming for further emissions reduction beyond the ambition of well below 2°C” (page 316) and category III as “contributing to Paris Agreement goal of pursuing efforts to limit to a 1.5°C temperature change“(page 316), other studies critically discuss whether the emission reduction changes can actually be considered to be in line with the Paris Agreement (Wachsmuth, 2018). A more recent forthcoming study[286] concludes that it is questionable that the scenarios other than the net-zero emission scenarios are Paris-Agreement-compatible.

These scenarios - all envision different levels of ratcheting up current mitigation efforts of the EU - are compared to a **baseline scenario** which is based on the “Reference scenario 2016”[287] (referred to below as “REF2016”), mainly reflecting the current EU decarbonisation trajectory.[288]

Wachsmuth and co-authors assess the **underlying assumptions** of the EC in-depth analysis and underlying the sectoral pathways (Wachsmuth et al., 2019). They conclude that with regard to energy supply, none of the presented scenarios makes full use of renewable energy combined with energy demand reductions, which could support limiting the deployment of negative emission reduction technologies. Moreover, they question the assumption of increasing nuclear power capacities in the EU after 2030 given social resistance and the unfriendly financing conditions for nuclear. For the building and transport sector, (Wachsmuth et al., 2019) find the conclusions to be plausible as they are in line with the literature. For the industry sector they argue that radical pushes for innovation will be needed as currently available technologies are not yet sufficient to deliver the switch from fossil fuels to renewables. For agriculture, Wachsmuth and co-authors note that certain options such as crop management and improving

[285] See Wachsmuth for a critical discussion on whether the emission reduction changes can actually be considered to be in line with the Paris Agreement (Wachsmuth, 2018)

[286] Wachsmuth, Jakob; Eckstein, Johannes; Duwe, M.; Freundt, M. (2019): Assessment of selected aspects of the Strategic Vision “A clean planet for all” of the European Commission. To be published by the German Environment Agency (Wachsmuth et al., 2019)

[287] The "EU Reference Scenario 2016 – Energy, transport and GHG emissions - Trends to 2050" (Capros et al., 2016) https://ec.europa.eu/energy/sites/ener/files/documents/ref2016_report_final-web.pdf

[288] This is based largely on agreed EU policies, or policies that have been proposed by the EU Commission but are still under discussion in the European Parliament and Council, however not yet including some recent national policies (European Commission, 2018a).

soil management are not included in the list of measures and moreover trade-offs between suggested mitigation options and impacts e.g. with regard to biodiversity or animal welfare are not sufficiently taken into consideration (Wachsmuth et al., 2019). Also, only one scenario (1.5LIFE) assumes changes in consumption patterns. For land-use, (Wachsmuth et al., 2019) highlight the strong role for energy crops for bioenergy and critisise that the CO2 removal rate is not discussed sufficiently. Concerning the role of negative emission technology (NET) deployment, BECCS[289] and DACCS[290] are the only NET options considered while others such as enhanced weathering or biochar are disregarded. The 1.5TECH scenario builds on substantial carbon removal, yet , Wachsmuth and co-authors conclude that the EC in-depth analysis relies on rather moderate underground storage for CO2 compared to studies estimating the geological potential for CO_2 storage in the EU. Moreover, technology assumptions have been subject to a review process. They however criticize a lack of transparency with regard to key input and output parameters such as sectoral activities and energy demands (Wachsmuth et al., 2019). Moreover, assumed discount rates on private investments for the building sector are considered to be relatively high. Additionally, the exclusion of the 1.5LIFE scenario from the macro-economic assessment is a limitation for comparing net-zero scenarios.

The scientific publication by Capros et al (2019) shows some more details for the PRIMES model based on scenario results that they had prepared as part of the analytical material to inform the long-term strategy of the European Commission ('A clean planet for all'). They highlight that the current climate and energy package of the EU for 2030 is not sufficient to reach the coal of climate neutrality in 2050. Moreover, they stress that some of the technologies included in the analysis are of low or medium technological readiness and that the role of investment and policies fostering investments will be crucial. Especially for the industry sector, technology which could have a disruptive character are not yet mature (Capros et al., 2019).

Macro-economic impact analysis

The **baseline scenario** for the macro-economic analysis assumes that the Intended Nationally Determined Contributions (INDCs) are implemented as reported to the UNFCCC and as modelled by the POLES-JRC model. It was constructed using results from the energy system model PRIMES.

For the macro-economic analysis, the analysed **mitigation scenarios** are limited to a subset of two out of the above mentioned eight scenarios (ELEC and 1.5TECH), representing two different levels of ambition: 2°C and 1.5°C (which the EC considers to represent 'net carbon neutrality by 2050' (see Table 30). Note that for the 1.5°C scenario, all remaining GHG emissions by 2050 need to be compensated for by negative emissions. For this, the selected 1.5TECH scenario relies substantially on the deployment of BECCS and CCS to reach net GHG neutrality by 2050.

[289] Bioenergy with Carbon Capture and Storage (CCS)

[290] Direct Air Capture with CCS.

Table 30: Scenario set assessed in macro-economic impact assessment

Scenario name	Ambition level	Main characteristics
ELEC	**2°C goal**: Reduction in GHG emissions of 81% by 2050 relative to 1990	• Electrification in all sectors • Higher energy efficiency post 2030 • Deployment of sustainable, advanced biofuels • Moderate circular economy measures • Digitalisation
1.5TECH	**1.5°C goal**: Reduction in GHG emissions of around 94% by 2050 relative to 1990 ('net GHG neutrality by 2050')	• BECCS and CCS, plus Cost -efficient combination of several measures (see Table 31) • Market coordination for infrastructure deployment • BECCS present only post-2050 in 2°C scenarios • Significant learning by doing for low carbon technologies • Significant improvements in the efficiency of the transport system
Baseline	Implementation of **INDC**s	

Source: (European Commission, 2018a).

Moreover, two different **states of fragmentation** of global efforts are differentiated, respectively.

- 'Macro-fragmented action scenarios': the rest of the world adheres only to nationally determined contributions as submitted to the UNFCCC, in parallel to EU ambitions
- 'Global action scenarios': the rest of the world achieves reductions of 46% or 72% in parallel to EU ambitions

Combined with the two ambition levels of EU climate action, this results in four mitigation scenario combinations for the macro-economic analysis:

Table 31: Mitigation scenario combinations depending on ambitions level and fragmentation of global efforts

Scenario name	Fragmented Action		Global Action	
Temp. target	**2°C goal**:	**1.5°C goal**:	**2°C goal**:	**1.5°C goal**:
EU	-80% in GHGs in 2050 vs 1990	'Net GHG neutrality' (-94%)	-80% in GHGs in 2050 vs 1990	Net GHG neutrality
Rest of the world	NDCs	NDCs	-46% in GHGs in 2050 vs 1990	-72% in GHGs in 2050 vs 1990

Source: (European Commission, 2018a).

17.6.1.1.4 Results

Overall, the EC in-depth analysis to the strategic vision states that a GHG-neutral European Union is not just technologically feasible but also achievable in a socially just and cost-efficient way. While a range of different impacts is assessed, we here focus on those that reflect mitigation costs concepts similar to those used in the rest of the report part.

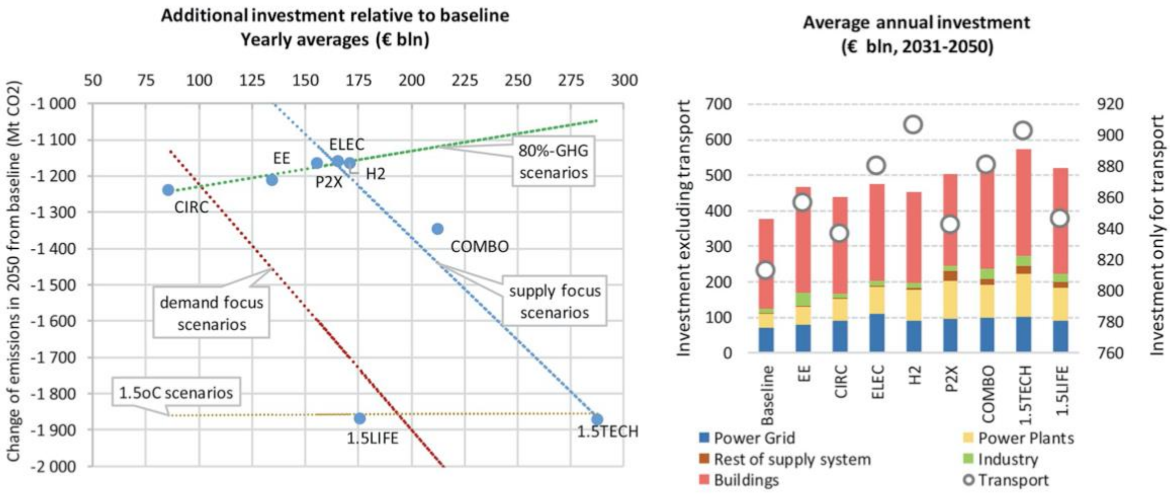
The objective of comparing the different scenarios is to show the different options of technological transition pathways available to the different sectors. While the analysis of **carbon prices** is not the focus of the EC in-depth analysis, some limited information is provided.[291] The carbon price represents a stylised price signal which leads to cost-effective deployment of low carbon technologies by the power and industry sector, for the given assumed availability of technologies and alternative energy carriers which vary for different scenarios depending on scenario characteristics (see Table 30). The development of the carbon price is one of the key drivers to reduce emissions in these scenarios, yet not the only driver. Reported carbon prices refer mainly to EU-ETS-sectors. Emission reductions in sectors not covered by the EU-ETS are mainly driven by other policy assumptions. The stylised carbon price signal assumed in the EC-in-depth analysis is at 28 EUR/tCO2 in 2030 – the start year for the actual scenario analysis. This level takes into account that there are interaction effects with other policies in the short to medium run, notably policies for energy efficiency and renewable energy targets in the EU for 2030. This means that the value of the carbon price cannot be considered to reflect the full marginal costs of mitigation as part of the abated emissions are achieved by policies other than the carbon price. After 2030, the carbon price signal increases to 250 EUR/tCO2 in 2050 for scenarios achieving between 80% and the 85% GHG reduction (excluding land use). For scenarios that achieve net-zero GHG emissions by 2050, it rises to 350 EUR/tCO2. In reality, actual carbon price developments will depend on a multitude of factors among others the implementation of other policies and how these affect technology costs and technology diffusion. For the macro-economic analysis, the macro-economic model JRC-GEM-E3 is run independently from the energy system model. In the macro-economic model carbon prices are applied to drive the mitigation of GHG emissions for the whole economy (for example by triggering shifting investments or changes in consumption and production patterns). Yet, the GEM-E3 model also builds on a range of results from the PRIMES model as exogenous input, including for instance how the shares of technologies in the power generation mix develop over time. Carbon prices are also stylised, however, in contrast to the core analysis based on the PRIMES model described above, carbon prices in the macro-economic analysis with GEM-E3 are the driver for both ETS and non-ETS sectors. For the EU, ETS and non-ETS carbon prices are set equal after 2030.

For mitigation costs in the form of **investment costs,** the EC in-depth analysis finds that based on PRIMES on average across the mitigation scenarios aiming for 80% reductions in emissions by 2050, an additional yearly investment of about 143 billion Euro (equivalent to an increase of 12% in total investment) as compared to the baseline scenario would be needed – with differences between scenarios ranging from a minimum of 86 billion Euro (for the circular economy pathway) to 171 billion Euro (for the H2 pathway). This would however be lower than the additional investment needs for achieving the 2030 targets. For the net-zero pathways, the additional annual investment range from 176 billion Euro (for the 1.5LIFE scenario) to EUR 290 billion (for 1.5 TECH) (European Commission, 2018a). Figure 90 from Capros et al. (2019) shows average annual investments costs for the different scenarios and different sectors (right) and compares the investment costs to reduced emissions for the different scenarios (left). On the other hand, there are estimated cost savings of about 1.4-3 trillion Euros (cumulated from 2031-

[291] This information is partly taken from Section 7.2 of the EC in-depth analysis (European Commission, 2018a) and has partly kindly been provided by the European Commission in an email exchange.

2050) from **reducing import dependency** for energy to about 20% in 2050 (European Commission, 2018a). Capros and co-authors state that the EU's yearly bill for fossil fuel imports – which by 2030 is expected to be over 2.5% of the EU's total GDP – would be reduced to 0.8% of GDP for the net-zero scenarios (Capros et al., 2019).

Figure 90: Overview of total investment expenditures in the EU for EC vision 2050



Source: Figure 12 from Capros et al. (2019) based on PRIMES scenario analysis for European Commission (EC).[292]

The **macro-economic analysis** of the EC in-depth analysis (European Commission, 2018a) also includes information on **investment cost**, identifying different driving assumptions:

- *Investment costs and impacts on private consumption (macro-analysis).* As JRC-GEM-E3 assumes that there are no unused capacities or inefficiently used resources in the economy, any increase in investments in one sector leads to a decrease of investments elsewhere or a reduction in private consumption (full crowding out effect). Investment costs seem higher in case of a fragmented regime as compared to global action, while consumption losses are suggested to be higher in a global effort regime (JRC-GEM-E3). In contrast, the E3ME model assumes that economies typically do not exploit full capacities at all times and allows for an increase in investments without crowding out other investments or consumption. Under the E3ME model, private consumption could rise by up to about 1.5% in 2050 relative to the Baseline (global action, 80% reduction scenario) (European Commission, 2018a).

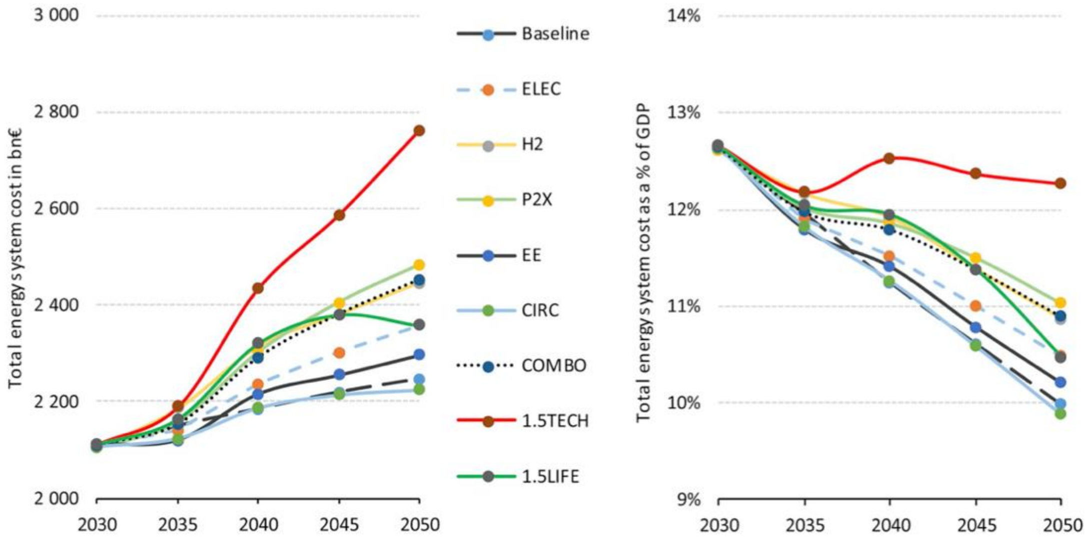
- *Investment costs and negative emission technologies (macro-analysis).* The EC choosing the 1.5TECH scenario instead of the 1.5LIFE scenario – which is the second net GHG neutrality scenario in the overall assessment scenario set – can be interpreted as 'pessimistic' with regard to investment costs as in the sense that the 1.5LIFE scenario assumes a stronger development of consumption patterns and industry towards sustainable consumption and circular economy, while the reliance on (costly) Negative Emission Technologies (NETs) instead would likely imply higher mitigation costs. However, as discussed above under 'fragmented regime' the additional investments can act as an economic stimulus boosting economic growth, leading to positive GDP effects. The highly aggregated measure of GDP impacts may thus mask different types of costs and (beneficial) feedback effects interacting -

[292] Permission to use this figure was obtained under the licence number 5012561337630.

all again dependent on the underlying assumptions of these feedback effects. This illustrates one of the shortcomings of using GDP losses as a measure for mitigation costs, showing that it is ideally complemented by other cost indicators to get a more complete picture of mitigation costs beyond macro-economic growth impacts.

Regarding **additional total energy system costs,** Capros and co-authors find that in all eight main decarbonisation scenarios rise beyond the energy system costs in the baseline scenario, with capital expenditure being the main drivers behind the increase (variable costs decrease) compared to baseline (Capros et al., 2019) (see Figure 91). Despite large uncertainties, total costs in scenarios focusing on demand side are lower compared to costs focusing on supply side.

Figure 91: EU total energy system costs



Source: Figure 10 Capros et al. (2019) based on PRIMES scenario analysis for EC. [293]

The estimated **macro-economic impacts in terms of GDP losses** compared to the baseline lie in a similar order of magnitude for all three models as well as all four scenario combinations, ranging from -1.3% to positive impacts of close to 2.2% (see Table 32 below). Even the strongest negative impact that was estimated would thus be moderate, as it would suggest that the EU's real GDP would be about only 1.3% lower in 2050 in case of strong mitigation actions as compared to the baseline of INDC implementation (JRC-GEM-E3, 1.5°C global action scenario). Looking at GDP impacts over time, the model JRC-GEM-E3 suggests that GDP losses gradually increase over time, meaning that the negative impact in 2050 is higher (in absolute terms) than the estimated impact in the years before 2050 in this model. The most positive estimate suggests that real GDP could be about 2.2% higher in 2050 than in the baseline (E3ME, 1.5°C global action scenario). Regarding impacts over time, the E2ME model suggests the highest positive impacts in about 2045 for the 'net GHG neutrality' global action scenario amounting to 3%, to then decrease slightly due to the repayments of loans. While the difference between estimates overall is small, the highest difference in results between different modelling approaches can be observed for the 1.5°C temperature limit scenarios: JRC-GEM-E3 model finds higher GDP losses for 1.5°C compared to 2°C, in contrast to the other models finding higher positive GDP impacts for 1.5°C.

[293] Permission to use this figure was obtained under the licence number 5012561337630.

Table 32: Mitigation scenario combinations depending on ambitions level and fragmentation of global efforts

	Fragmented Action		**Global Action**	
Temp. limit	**2°C goal**:	**1.5°C goal***:	**2°C goal**:	**1.5°C goal***:
EU	-80% in GHGs in 2050 vs 1990	'Net GHG neutrality' (-94%)	-80% in GHGs in 2050 vs 1990	Net GHG neutrality
Rest of the world	NDCs	NDCs	-46% in GHGs in 2050 vs 1990	-72% in GHGs in 2050 vs 1990
Models	Estimated GDP loss in EU in 2050 compared to baseline (NDCs)	Estimated GDP loss in EU in 2050 compared to baseline (NDCs)	Estimated GDP loss in EU in 2050 compared to baseline (NDCs)	Estimated GDP loss in EU in 2050 compared to baseline (NDCs)
JRC-GEM-E3	-0.13%	-0.63%	-0.28%	-1.3%
E3ME	1.26%	1.48%	1.57%	2.19%
QUEST	0.31%	0.68%	/	/

Estimates for JRC-GEM-E3 show deviation from Baseline in % of GDP for the model variant that assumes maximisation of profit in ETS sectors, flexible wages in the long run and lump-sum transfer of carbon revenue to households.
*The EC in-depth analysis labels the 'net GHG neutrality' scenarios to be in line with a 1.5°C temperature limit. However, this has been questioned by other studies (see Section 17.6.1.1.3 on scenarios).
Source: (European Commission, 2018a)

The authors of the analysis therefore conclude that the modelling results "convey a consistent message: the impacts of decarbonisation on GDP will be limited" (European Commission 2018, 218), regardless of the scenario. All the models indicate that the EU reaching net GHG neutrality would impose only comparably minor GDP losses, or could even have positive effects on GDP. Also, unilateral action of the EU ('fragmented action') would only lead to limited GDP losses according to the model JRC-GEM-E3. To furthermore put the impacts into perspective, the in-depth anaylsis of the EC calculated for illustration that decarbonisation would lead to the EU economy growing in the worst case by 66.0% between 2015 and 2050 instead of 68.1% under the Baseline (JRC-GEM-E3, 1.5°C global action scenario), or growing in best case by 73.7% instead of 70.7% (E3ME, 1.5°C global action scenario) and growing by 69.3% instead of 68.4% (QUEST, 1.5°C scenario). Using 1990 as a reference year, net GHG neutrality could be achieved by 2050 despite the economy growing by 152% to 163%. In terms of per capita increases, this would mean that GDP per capita increases 126% to 136% (European Commission, 2018a).

Though the absolute differences in results between models and scenarios are very moderate, some **factors that influence cost estimates** can be identified:

- **Assumptions on efficient markets**. The CGE model JRC-GEM-E3 suggests slightly negative impacts on GDP by 2050. In contrast E3ME and QUEST both indicate that the impact on GDP could actually be positive, even for the scenario of 'net GHG neutrality'. The reason why the direction of the impact differs between models results from different assumptions on market imperfections and whether all resources are optimally used in the economy (i.e. no inefficiencies exist).[294]

- The results moreover suggest differences between the scenario assumption about **fragmented action versus global common efforts**. Different model assumptions with regard to impacts on global output, competitiveness and market size lead to different underlying effect here[295].
- **Revenue Recycling and labour market imperfections.** A sensitivity analysis conducted using JRC-GEM-E3 suggests that revenue recycling of carbon revenues can create a slightly positive impact on GDP, when the model allows for labour market imperfections as taxes on labour can be lowered, generating a positive effect on GDP as distortions in the labour market are reduced (European Commission, 2018a).

In summary, the results show that despite differences in modelling assumptions and ambition levels, all mitigation cost estimates lie rather close together, while impacts are estimates to be slightly negative or positive depending on whether the model assumes that the economy is in equilibrium, leading per construction to negative impacts if policies are imposed or whether the economy exhibits inefficiencies, allowing for negative cost options and positive impacts. Moreover, aggregate measures such as GDP losses can be misleading as they mask the underlying processes and cost distributions.

17.6.1.2 European decarbonisation pathways under alternative technological and policy choices: A multi-model analysis (Capros et al., 2014b)

17.6.1.2.1 Research Question

The objective of the scientific article (Capros et al., 2014b) and the companion study describing the underlying seven energy economy models frequently used for EU-related analyses (Capros et al., 2014a) is to systematically analyse decarbonization pathways for the European energy system until 2050 in a multi-model comparison. It assesses the required energy system transformations and the associated costs for the EU for meeting the decarbonisation targets of the EU Roadmap 2050 (80% GHG emissions reduction by 2050). Main focus is analysing the impact of technology limitations and delays in climate policy.

[294] As an optimization model, GEM-E3 assumes that the economy is in equilibrium and all resources are used efficiently (assuming perfectly functioning markets). By construction, climate policy triggers a deviation from this equilibrium by reallocating production factors between sectors, imposing costs as compared to the baseline. The model E3ME in contrast assumes that there can be unused resources in the economy, leading to additional investment in decarbonisation functioning as a demand stimulus and thus triggering additional economic growth. However, the additional investments are financed by borrowing, creating a negative stimulus at a later stage when loans are repaid. QUEST likewise assumes that there is a positive expenditure stimulus ('shock') generated by decarbonization investments (European Commission, 2018a). Despite different signs, the actual differences between the estimates from all three models are, however, small.

[295] The model JRC-GEM-E3 suggests that GDP impacts could be less pronounced in case of unilateral action of the EU compared to global action. In this model, higher mitigation ambitions lead to higher costs for internationally traded goods which negatively affects the competitiveness of local producers. However, in case of global action, the global economy and thus also export markets are negatively affected by mitigation costs. The model assumption that the effect of the EU's market size outweighs the effect of competitiveness losses, leads thus to lower GDP losses for the EU in case of fragmented action (European Commission, 2018a). Furthermore, also the baseline scenario assumes some climate action (NDC implementation) by the EU. However, (European Commission, 2018a) also highlights that the impacts for different sectors vary, with fossil fuel industries seeing much higher losses in terms of sectoral output (between -32.6% and -54.5%), while other industries such as electricity supply or construction would see positive output effects of up to close to 30% for electricity supply (JRC-GEM-E3 model). In contrast, the mechanisms in E3ME are different; investments for decarbonization create an economic stimulus due to the assumption of existing spare capacities. The global mitigation efforts then lead to higher outputs in the rest of the world as compared to unilateral action by the EU. The positive impact of growing market size and the positive impact of global mitigation efforts generate a higher stimulus for the EU than fragmented action in E3ME.

17.6.1.2.2 Approach

The systematic multi-model analysis comprises the two partial equilibrium energy system models PRIMES and TIMES-PanEU, the two energy models focusing on specific sectors GAINS and Green-X, and the two comprehensive CGE models GEM-E3 and WorldScan as well as the macro-econometric model NEMESIS.

The different models have their specific strength but also limitations, and can be used for complementary analysis. As partial equilibrium models, the energy system models PRIMES and TIMES-PanEu do not capture feedback effects on the economic system and resulting costs, but with their detailed representation of engineering constraints, technology portfolios and disaggregated simulation of energy markets, they serve well to answer technology related questions (such as required storage, grid enhancement and intermittency) and energy system costs for decarbonization efforts in the EU. The Green-X models offers a bottom-up simulation for renewables deployment in the EU member states. The GAINS model features an explicit representation of thousands of mitigation technologies and projects related to non-CO2 GHG emissions. GEM-E3, WorldScan and NEMESIS in contrast have a rather simplistic approach to model RE integration, but they allow quantifying the macro-economic impacts of decarbonisation policy for the EU (i.e. in terms of changes in GDP and consumption and in employment, investments and production for each economic sector). GEM-E3 and WorldScan include an endogenous representation of the global economy which allows to quantify the impacts on the EU economy resulting from global mitigation action and competitiveness impacts for exports. The detailed energy system models are thus used to verify the feasibility of energy results obtained from the macro-economic models. Main differences in methodological approaches and assumptions are related to technological details in the energy sector, substitutability assumptions of energy sources and the representation of GHGs.

17.6.1.2.3 Scenarios and core assumptions

The multi-model study defines a set of scenarios for the analyses (summarized in Table 33): i) a reference scenario (AM5S1) including the already decided energy and climate policies in the EU Member States, ii) a basic decarbonisation scenario (AM5S2) with full availability of all technological decarbonisation options and those being used based on cost efficiency, thus representing the least-cost decarbonisation pathway for the EU, iii) different decarbonisation scenarios (AM5S3, AM5S6) assuming various technology limitations such as nuclear power phasing out, CCS technologies not being commercially available and delays in transport electrification and iv) two decarbonisation scenarios assuming that climate policy is delayed until 2030 (AM5S7,AM5S8). Carbon pricing is assumed to apply to ETS and non-ETS sectors for optimal cost-efficiency, with equal values for EU-ETS sector and non-EU-ETS sectors and all EU member countries from 2025 onwards. Assumptions on energy efficiency and RE deployment vary between scenarios.

All decarbonisation scenarios are designed to meet the same carbon budget (2010 to 2050), in line with the cumulative emissions from the 2050 Roadmap for the EU. For the reference scenario, GHG emissions decrease by about 40% below the 1990 levels in 2050 (according to PRIMES, TIMES-PanEu and GEM-E3), which is about half the effort needed to fulfil the EU decarbonization target of 80% by 2050.

Table 33: Scenario specifications and decarbonization options in Capros et al.

	Reference scenario	Decarbonisation scenarios						
	AM5S1- reference	**AM5S2**	**AM5S3**	**AM5S4**	**AM5S5**	**AM5S6**	**AM5S7**	**AMS58**
Assumptions on EU climate policies and targets	- EU adopted policies up to 2020 (Energy and Climate Policy Package) - After 2020 linear annual reduction of ETS cap (-1.74% p.a.) - No additional RES and EFF policies - Non-ETS emissions remain below the cap specified for 2020	- The Roadmap carbon budget is imposed in 2010-2050 - All emission reduction options are available - Their mix follows least-cost approach	- The Roadmap carbon budget is imposed in 2010-2050 - Higher efficiency and RES compared to AM5S2 - Low CCS and nuclear	- The Roadmap carbon budget is imposed in 2010-2050 - Maximum energy efficiency - No CCS and nuclear phase-out	- The Roadmap carbon budget is imposed in 2010-2050 - Maximum RES deployment - No CCS and nuclear phase-out	- The Roadmap carbon budget is imposed in 2010-2050 - Limited transport electrification	- The Roadmap carbon budget is imposed in 2010-2050 - Delayed climate action untiL 2030, then all decarbonization options available	- The Roadmap carbon budget is imposed in 2010-2050 - Delayed climate action until 2030, then no CCS and nuclear phase-out
Assumptions on climate policies undertaken by the rest of the work	- Low end of Copenhagen-Cancun pledges until 2020 - No climate policy intensification after 2020 (moderate climate action)	Strong decarbonisation efforts for achieving the 450 ppm stabilisation target	Same as in AM5S2	Same as in AM5S2	Same as in AM5S2	Same as in AM5S2	Delayed action until 2030, then according to the 450 ppm stabilisation scenario	
Assumptions on energy efficiency		Optimal	Highest possible	Highest possible	Optimal	Optimal	Optimal but delayed	Highest possible, but delayed
RES deployment		Optimal	Highest possible	Optimal	Highest possible	Optimal	Optimal but delayed	Highest possible, but delayed
Nuclear power deployment		Optimal	Low	Phase out	Phase out	Optimal	Optimal but delayed	Phase out
Deployment of CCS technologies		Optimal	Low	No	No	Optimal	Optimal but delayed	No
Electrification in transport		Full	Full	Full	Full	No	Full	Full

Source: (Capros et al., 2014b).

17.6.1.2.4 Results

Despite required profound structural changes in the EU energy system, a robust finding from all models is that the EU Roadmap 2050 decarbonization target is technically and economically feasible based on current technology options. All models manage to meet the emission reduction target at relatively modest costs being lower than 1% of GDP (2010-2050 in cumulative terms).

All models confirm that it is a cost-efficient strategy to decarbonise the power generation sector through higher renewable deployment and CCS technologies in order to replace fossil fuel use in more inflexible energy demand sectors such as transport by (low carbon) electricity. It also confirms the important role of energy efficiency improvements. All models find that in the basic decarbonisation scenario there remain unexploited large energy efficiency improvements and renewable potentials. Constraining CCS, nuclear and transport electrification, all models need to exploit RE and energy efficiency potentials to a higher level implying higher carbon prices and energy system costs (partly due to higher costs for required grid investments, power system stability and storage needs due cope with high RE shares).

Meeting interim decarbonisation targets for 2030 would lead to very small additional energy system costs and GPD losses (below 0.3% of GDP) until 2030 in all models relative to the reference scenario.

Assessing **the impact of delaying EU climate policy efforts until 2030**, the energy system models show that this would have serious impacts on costs as the main effort in meeting the carbon budget would be falling into the shorter period 2030 to 2050, requiring very steep emission reductions after 2030. As a consequence, higher carbon prices after 2030 are required, and lock-in effects in the energy sector and delays in the technological progress for renewables and CCS occur, leading to energy system costs increasing by 0.6%-points of GDP between 2010 and 2050 compared to the optimal policy scenario without delay. Carbon prices in the case of delayed climate action (AM5S7) follow the trajectory of the reference scenario up to 2030, but after that steeply increase between 2030 and 2050 reaching 962 $EURO_{2005}/tCO_2$ in PRIMES and almost 700 $EURO_{2005}/tCO_2$ in TIMES-PanEu.

If in addition to the climate action delay there would be technology constraints on CCS and nuclear (AM5S8), impacts on energy system costs in the case of a policy delay until 2030 would be very high meaning an increase by about 2%-points of GDP according to PRIMES. Also, carbon prices are projected to reach extremely high values[296] in this case. These results highlight the importance of strong near-term climate policy efforts accompanied by developing the required infrastructure before 2030 to avoid prohibitively high costs which may result from a delay.

[296] Exact numbers not reported in Capros et al. (Capros et al., 2014b), but described as ‘skyrocketing’.

Table 34: EU Carbon prices in 2030 and 2050 (in 2005-Euros/tCO2)

	Basic decarbonisation scenario (AM5S2)	AM5S3	AM5S4	AM5S6	AM5S7
	All emission reduction options available, their mix follows least-cost approach	*Higher efficiency and RES compared to AM5S2; Low CCS and nuclear*	*Maximum energy efficiency; Nuclear phase out and no CCS*	*Limited transport electrification*	*Delayed climate action until 2030, then all decarbonisation options available*
Carbon prices in 2030:					
PRIMES	49.2	30.3	50	65.0	As reference trajectory (not reported)
TIMES-PanEu	20.8	97.4	82.3	22.2	As reference trajectory (not reported)
NEMESIS	60.4	39.2	39.2	-	-
GEM-E3	91.4	64.1	80.4	185.4	-
WorldScan	29.0	-	-	-	-
Carbon prices in 2050:					
PRIMES	259.9	231.9	354.9	299.9	962
TIMES-PanEu	565.4	251.3	1043.2	770.2	700
NEMESIS	-	-	-	-	-
GEM-E3	243.0	210.8	514.7	1601.3	-
WorldScan	-	-	-	-	-

All scenarios assume that carbon budget of the 2050 EU Roadmap is imposed for 2010 to 2050. Prices are all reported in 2005-EUROS per ton of CO_2.

Source: Compiled from (Capros et al., 2014b).

shows the carbon prices for the years 2030 and 2050 for the different scenarios for which information was provided by Capros and co-authors (Capros et al., 2014b). Table 35 shows impacts on GDP.

Table 35: Impact of technology limitations on EU GDP

Cumulative % changes in EU GDP (2015-2050) compared to GDP of basic decarbonization scenario (AM5S2)

Scenario	Scenario characteristics	GEM-E3 (until 2050)	WorldScan (until 2030)	NEMESIS (until 2030)
AM5S3	*Higher efficiency and RES compared to AM5S2; Low CCS and nuclear*	-0.27	-0.30	-0.05
AM5S4	*Maximum energy efficiency; Nuclear phase out and no CCS*	-0.43	-0.26	-0.10
AM5S5	*Maximum RES deployment, Nuclear phase out and no CCS*	-0.13	-0.29	-0.06
AM5S6	*Limited transport electrification*	-0.73		

Source: (Capros et al., 2014b)

The journal article also discusses **differences in model results stemming from differences in model structure and underlying assumptions**. Macro-economic models do not feature the detailed energy system dynamics from energy system models and instead rely on aggregated functions such as CES[297] functions. To mimic the flexibility of substitution simulated in bottom-up energy system models, high very high numerical values for elasticities of substitution in the CES functions are needed in macro-economic models. This leads to higher rigidities of CES and higher marginal abatement costs typically leading to higher carbon prices in macro-economic models compared to energy system models for the same mitigation of emissions.

Until 2040, PRIMES and TIMES-PanEu project similar carbon price trajectories, but then diverge between 2040 and 2050. In TIMES-PanEu, the incremental abatement potential almost fully exhausted by 2040, requiring it to impose much higher carbon prices in 2040 to 2050 compared to PRIMES. GEM-E3 projects lower carbon prices than TIMES-PanEu for 2050. This can be explained by GEM-E3 featuring bottom-up formulations representing strong energy efficiency improvement and transport electrification acting additionally to the effects from constant elasticity of substitution mechanisms.

WorldScan finds higher GDP losses (amounting to close to 1% of the reference GDP by 2030) compared to other models. Capros and co-authors explain this by WorldScan being characterisied by high substitution rigidities and a lack of bottom-up representation of the energy system mechanisms (Capros et al., 2014b). NEMESIS finds lower GDP losses until 2030 compared to GEM-E3. (Capros et al., 2014b) identify the following reasons for this: i) differences in the underlying theoretical foundation (neo- Keynesian vs. General Equilibrium) leading to differences in assumptions on crowing out effects for investments[298], markets and with regard to current account deficits, ii) GEM-E3 models adverse effects on the EU economy resulting from global climate action (reducing global demand and affecting EU exports) endogenously in contrast to NEMESIS; iii) assumptions on recycling scheme used to redistribute carbon revenues differ between the models.[299]

[297] Constant Elasticity of Substitution.

[298] NEMESIS assumes that it is possible to have large decarbonization induced investments in the energy sector without leading to a diversion of investments from other sectors. As a general equilibrium model assuming optimality, in GEM-E3 crowding out effects occur.

[299] GEM-E3 assumes that carbon revenues are recycled back to households as lump-sum transfers, while NEMESIS assumes that part of the carbon revenues is used to reduce labour costs.

17.6.1.3 Energy system transition and macroeconomic impacts of a European decarbonization action towards a below 2 °C climate stabilization (Vrontisi et al., 2019)

17.6.1.3.1 Research Question

The scientific publication (Vrontisi et al., 2019) assesses the transformation of the energy and economic system of the EU28 under a decarbonization pathway until 2050. Among other aspects, they analyse the macro-economic impacts of European decarbonization under two different global climate action pathways (considering the climate action of other major emitters) – one assuming that NDCs are implemented globally (fragmented action) and the second assuming that there is more ambitious coordinated global action in line with climate stabilization at well below 2°C. It moreover provides insights on the key sectors for decarbonization.

17.6.1.3.2 Approach

Vrontisi et al. (2019) use a one-way soft linking approach to combine the technology-rich detailed energy system model PRIMES and the economy-wide hybrid Computable General Equilibrium (CGE) Model GEM-E3.

PRIMES is a large partial equilibrium model for the European Union's energy system representing member states in detail. With a time horizon to 2050, it features comprehensive projections of energy demand, supply, system costs and investment as well as market prices, covering the whole energy system and the related emissions. PRIMES is described a s unique hybrid model that combines technological and engineering detail with micro- and macroeconomic interrelations. It reflects dynamics of top-down behavioural modelling together with engineering bottom-up modelling. PRIMES is able to include multiple policy targets, such as fuel standards, emission trading. It has been frequently used in assessments for the EU Commission.

GEM-E3 is a hybrid general equilibrium model that can provide insights on the macroeconomic and sectoral impacts with regard to interactions between the economy, the environment and the energy system. With the objective function of maximizing welfare for households and minimizing costs for firms, the GEM-E3 model simultaneously calculates the equilibrium in goods and service markets, as well as in the labor and capital markets. It is dynamic, recursive over time with a time horizon to 2050. It links different regions through endogenous bilateral trade. The version of GEM-E3 used in Vrontisi et al. (2019) includes 19 regions with 39 categories of economic activities (including separate representations of the sectors that produce low-carbon electricity supply technologies and electric vehicles). The model also includes a detailed representation of the power generation system (10 technologies) and a detailed transport module (private and public transportation). The EU-region was calibrated using EUROSTAT data. A distinctive feature of GEM-E3 is the representation of an imperfect labour market allowing for involuntary unemployment. The GEM-E3 environment module comprises all GHG emissions and a wide array of abatement options as well as different carbon market structure (e. g., grandfathering, auctioning, alternative recycling mechanisms).

For this study, both models have the same key macroeconomic assumptions and techno-economic characteristics for the EU28.

17.6.1.3.3 Scenarios and core assumptions

The journal article by analyses a Reference scenario and a set of EU28 well below 2 °C(*EU-WB2℃*) scenarios, which are implemented by both models (Vrontisi et al., 2019). The EU-WB2°C scenario differentiates between two different external climate action assumptions outside of the

EU (assessed by GEM-E3) assuming fragmented action at the level of ambition of NDC implementation (EU-WB2°C_NDC) or global coordinated ambitious action in line with well below 2°C (WB2°C_Global).

The *Reference scenario*, serving as a basis of comparison for alternative policy scenarios, reflects a pathway of key economic, energy and environmental indicators under current economic and climate policies[300] without accounting for submitted NDCs regarding the Paris Agreement. For the EU28, the Reference scenario is based on the 2015 "Aging Report" from the European Commission[301] and the EU 2016 Reference Scenario[302].

For the *EU-WB2°C* policy scenario, it is assumed that the EU NDC for 2030 is fully implemented (more explicitly referring to the implementation of the '2030 Climate and Energy Framework' as layed out in the 'Winter Package' of the European Commission in 2016).[303] For the time horizon until 2050, the PRIMES 2°C scenario is in line with the EU's 'Roadmap to 2050' which aims for achieving GHG emission reductions of 80% compared to 1990 levels.

The EU's carbon budget (i.e. the cumulated CO2 emissions) considered in line with well-below 2°C for the period 2015-2050 is defined exogenously. This budget, which excludes emissions from land use, land use change, and forestry (LULUCF), is defined as 81 Gt CO_2 (if emissions captured through carbon capture and storage technologies are also excluded the budget increases to 86 Gt CO2). Vrontisi and co-authors argue that this regional carbon budget would be in accordance with regional cost-optimal allocations and close to 'per capita convergence' estimates, however would be above the levels that are considered 'fair and equitable' by the literature (Vrontisi et al., 2019).

For non-EU regions, Vrontisi and co-authors develop two alternative policy scenarios reflecting different levels of international ambition, fragmented action compared to global ambitious action (Vrontisi et al., 2019).

For the first policy scenario version (*fragmented action*), GEM-E3 simulates the complete implementation of the conditional NDC pledges for all G20 countries for the economic sectors in the NDCs. For other model regions, the model assumes that no additional policies are implemented beyond the reference scenario. After 2030, for non-EU countries, a continuation of the fragmented climate action is assumed implementing the same GHG reduction rates found in the Reference scenario for 2030 in all following years.

For the second policy scenario (*WB2°C_Global*), global mitigation action in line with a well below the 2 °C stabilization (67% chance) is assumed, applying a global carbon budget of 810 Gt CO_2 for the period 2016–2100, corresponding to a global carbon budget of 675 Gt CO2 (excluding LULUCF) until 2050 according to pathways from the literature. A global, economy-wide carbon price on all GHGs and sources from 2025 onwards is implemented to achieve the imposed emission constraint. Before 2025, the policies from the Reference scenario are assumed. Despite

[300] The PRIMES model incorporates a detailed list of energy and climate policies at EU level and EU28 member states' level until end of 2014. In the GEM-E3 model, the Reference scenario for EU28 is based on common assumptions regarding total and sectoral economic growth, population development, and total GHG emissions, energy, and carbon prices. For non-EU regions in GEM-E3, the Reference scenario builds on literature using exogenous assumptions of main socioeconomic drivers, including GDP, population and energy efficiency, and information on current energy and climate policies outside of the EU excluding NDCs.

[301] The 2015 Ageing Report: Economic and budgetary projections for the 28 EU Member States (2013-2060), see https://ec.europa.eu/economy_finance/publications/european_economy/2015/pdf/ee3_en.pdf

[302] Capros P. et al. (2016). EU Reference scenario 2016: energy, transport and GHG emissions - trends to 2050. European Commission 27. doi:https://doi.org/10.2833/9127

[303] Main targets for the year 2030: (i) an EU-wide GHG emission reduction by 40% compared with 1990 levels, (ii) a GHG emission reduction by 43% compared with 2005 for EU Emissions Trading Scheme (ETS)-sectors and a 30% reduction in the non-ETS sectors respectively, (iii) a renewable energy share target of 27% RE in gross final energy demand, and (iv) an energy efficiency target of 27% reduction compared to 2007 European Commission Reference levels.

the carbon budget referring to CO2 emissions only, this carbon price is applied to all non-CO2 GHGs as well.

In both policy scenarios simulated with GEM-E3 model, there is revenue recycling in form of tax revenues from carbon pricing being fed back into the economy by means of reducing indirect taxation.

17.6.1.3.4 Results

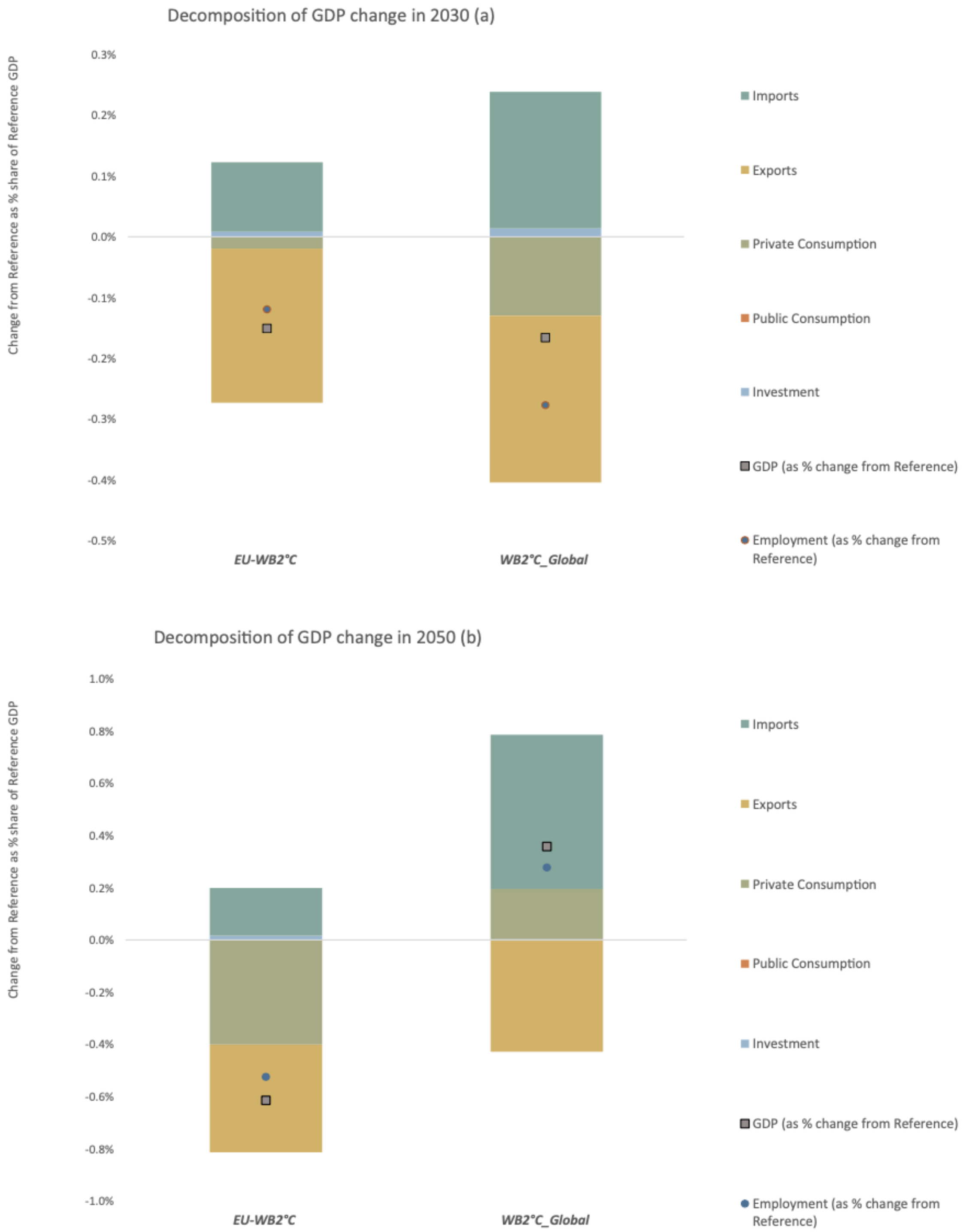
Vrontisi and co-authors find that emission reductions in the energy supply sector play a key role until 2030, then the transport sector gains importance until 2050. In 2050, emissions from transport and non-CO2 emissions are the main sources remaining (Vrontisi et al., 2019). Overall, they conclude that the emission reductions required for the 2°C stabilization could be achieved with technologies that are already existing and *would not* require use of negative emission technologies such as BECCS (biomass with CCS). This is in contrast to the role that negative emission technologies play in other studies e.g. in the IPCC reports.

With regard to total energy system cost (borne by final energy consumers), these are found to be slightly higher in the decarbonization scenario compared with the reference scenario. However, the difference is small and is below one percentage point of GDP even for the worst case. The rise in energy costs point to a potential crowding-out effect in the economy negatively affecting GDP, especially for fragmented climate action. At the same time, there is potentially a large substitution effect of replacing imported fuel by domestically produced parts for producing renewable energy and saving energy. This substitution effect could lead to a positive multiplier effect on employment.

They moreover find that **the impacts on the economy of the EU strongly depend on the mitigation action and ambitions of other major players as well as the relative carbon intensity across regions (see** Figure 92**)**. For the case of fragmented action with other major players limiting their ambitions to NDC implementation (representing asymmetric ambitions) while the EU strives for well below 2°C, this results in (small) economic losses for the EU28 compared to the ('pre-Paris') reference scenario (although the EU benefits from clean energy exports and reduced energy intensity). In case of global action towards well below 2°C, they find economic gains for the EU, despite the overall (global) emission reductions being considerably higher in 2050 (global GHG emissions fall by 72% compared to the Reference scenario). A key driver for this is that relative to other regions, the EU has lower energy GHG emission intensities (among the lowest globally) which are already observed for the Reference scenario. The EU economy would be well equipped to deal with global carbon pricing.

Vrontisi and co-authors emphasize that macro-economic impacts are strongly depend on the way carbon tax revenues are used with **revenue recycling** providing an important tool to mitigate negative impacts of climate policy. In their model, the revenues can reach up to 2.5% of the EU28's GDP (Vrontisi et al., 2019).

Figure 92: GDP impacts and decomposition for EU208



Decomposition of GDP changes in the EU28 in the scenarios EU-WB2°C (fragmented action) and WB2°C_Global (global action) relative to the Reference scenario for the years 2030 (a) and 2050 (b). The contribution of each GDP component is its change from Reference levels expressed as a share of Reference GDP. GDP and employment (markers only) are expressed in % change from Reference levels
Source: Figure 4 from Vrontisi et al. (2019) using the models E3MLab and GEM-E3 (Vrontisi et al., 2019).[304]

[304] Open Access article allowing use of figure under Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0/). No changes made to original figure; the caption has been slightly adjusted adding information on the scenarios.

17.6.1.4 "European electricity sector decarbonization under different levels of foresight" (Gerbaulet et al., 2019)

17.6.1.4.1 Research Question

Some modelers apply myopic expectations to reduce the computation time of their models, which again allows for incorporating an increasing level of detail in the model. However, this change in how foresight is modelled is typically associated with a substantial impact on the results, with studies finding differences relating to stronger reliance on conventional (fossil) energy sources and less new technologies being deployed leading to higher costs if myopic behaviour is applied (Gerbaulet et al., 2019).

The scientific publication Gerbaulet and co-authors analyses different (cost-effective) pathways for decarbonizing the European electricity sector until 2050. Specifically, it assesses the implications of different assumptions about foresight towards decarbonization targets on investment decisions in the European electricity sector (Gerbaulet et al., 2019). The authors compare the results assuming perfect foresight versus myopic expectations in relation to certain (political) decarbonization targets as well as assuming that CO_2 emissions can be freely allocated over the period between 2020 and 2050.

17.6.1.4.2 Approach

Gerbaulet et al. (2019) use a detailed dynamic partial equilibrium model of the European electricity sector named "dynELMOD" (dynamic Electricity Model). It is a dynamic investment and dispatch model with the objective of minimising total energy system costs in Europe until 2050. The model endogenously allocates investments to different power generation technologies, different types of storage (including demand side management), and the electricity transmission grid, determining in the next step the power plant dispatch as well as electricity transmission between countries. Focusing solely on the electricity sector in Europe, it features a high representation of underlying grid infrastructure on a country level and is able to reflect different types of foresight regarding investment decisions.

17.6.1.4.3 Scenarios and core assumptions

In Gerbaulet et al. (2019) three scenarios are analysed which reflect different degrees of planning foresight with regard to decarbonization pathways up to 2050. All scenarios assume a close to complete decarbonization of the European electricity sector by 2050 while assuming a moderate increase in electricity demand over time.

- The *default scenario* (reference scenario) assumes perfect foresight over the entire time horizon from 2015 to 2050, while the central decision maker is subject to a CO_2 constraint that is linearly decreasing every year, reducing CO_2 emissions to only 2% of the current level by 2050.
- The *reduced foresight scenario* assumes myopic decision makers that are only aware of CO_2 targets for the 5-year period ahead. This assumption is supposed to reflect potential short-sightedness of policy makers due to electoral cycles and investors' limited trust in political long-term targets.
- A third scenario represents a different way of allocating carbon emissions using a *budget approach.* This means that decision makers get an aggregated CO_2 emission budget for the

entire period 2015 to 2050 (here: about 22.5 bn tCO_2) and are free to allocate the emission allowances over time, but with the constraint that the annual emissions in 2050 should not exceed 2% of 2015 CO_2 emission levels.

17.6.1.4.4 Results

The different foresight assumptions applied by Gerbaulet and co-authors lead to different investment behaviours and produce different electricity sector structures. The analysis shows the advantages of a structured (long-term vision-based) energy transition compared to potentially short-sighted decision making.

Assuming myopic behaviour - i.e. a reduced awareness of future, longer term, carbon emission abatement needs (the *reduced foresight scenario*) - changes the resulting investment strategy because long-term decarbonization targets are not taken into account by actors. This results in substantially higher investments in carbon-based capacities, especially gas, leading to stranded investments of 75 GW of gas-capacities in the 2030s. In the scenario assuming free allocation over time (the *budget approach*), there is a sharp reduction in emissions between 2020 and 2030 - about 170 Mt lower than in the default scenario- however emissions increased above those in the default scenario between 2040 and 2045.

In all scenarios analysed Gerbaulet et al. (2019) found that renewables contribute the most to decarbonization, while nuclear power and carbon capture and storage were too costly to compete. Investments into new hard coal or lignite were not observed in any scenario. Accounting for climate targets renders investments into any additional capacity of conventional energy uneconomic from 2025 onwards, resulting in a coal and gas phase-out in the 2040s.

With regard to costs, the **overall system costs** over the entire period can be reduced by around 1% when free allocation over time is allowed which amounts to about 1.2 bn Euro per year for the entire model region.

The model also yields **implicit CO_2 prices** as shadow prices of the emission constraint. In the *default scenario* the reduction of the available CO_2 emissions leads to an increase in the implicit CO_2 price from 32 Euro/t (2020) to 177 Euro/t (2050). The *reduced foresight* scenario exhibits a comparable price development even though price increases occur at a later stage; between 2045 and 2050. For the *emission budget* scenario, there are no annual values reported, instead a price spanning the entire model period is given of approximately 34 Euro/t, reflecting the shadow price of an additional ton of CO_2 at any point during 2015 to 2050 (Gerbaulet et al., 2019).

17.6.2 Studies focusing on Germany

In the following, we present results of four recent German studies that use national mitigation models.[305] While these studies have a broader scope, we focus on the results concerning mitigation costs. An overview on additional German studies can be found in Table 12 of Ausfelder et al. (2017). Moreover, we highlight results from a sensitivity analysis for Marginal Abatement Costs (MAC) for the UK.

[305] Note that the following descriptions draw on the descriptions within these studies, which are originally in German.

Box 17: Sector-specific cost rates

The Paris Agreement temperature limit essentially demands economy-wide net-zero emissions by 2050. Therefore, essentially all sector must reach zero or near zero emissions, the remainder being accounted for by negative emission technologies. Text-book economics states that the tax level should be the same across all sectors to reach that limit in an economically efficient way. Yet, sectors have different barriers and pre-existing policies (standards, bans, subsidies, etc.), such that a temporary sector-specific tax may be more appropriate in these circumstances. It may also be politically more feasible. Finally, sector-specific taxes may be adjusted rather straightforwardly if emissions within the respective sector are not in line with the sectoral goal (if such a goal exists). In principle, a national mitigation cost model allows to provide such sector-specific cost rates (e. g. based on Figure 98).

17.6.2.1 Sector coupling — Analysis and considerations for the development of an integrated energy system[306]

17.6.2.1.1 Aims

Ausfelder et al., 2017 analyses which aspects are necessary for the success of energy system transformation. It scrutinizes the entire energy system in all its interrelationships and dependencies, considering the security of supply and limitation of costs. The study shows that sector coupling must play a much greater role in shaping the future energy system than it does today. Sector coupling refers to linking the sectors of electricity, heat[307] and transport.[308]

17.6.2.1.2 Modelling approach

The study postulates that four transformations play a major role:

- use of **electricity** as final energy not only for electrical applications, but also for heating and driving vehicles,
- conversion of electricity into **hydrogen** in order to use it as a final energy carrier in all sectors,
- the conversion of hydrogen into **synthetic fuels**, and
- energy production from **biomass**, **solar thermal energy** and **deep geothermal energy**.

It thus presents a quantitative and qualitative assessment of the suite of technical options and identifies technical, economic and social challenges. It demonstrates important system parameters and correlations, development paths, key technologies and system costs. Finally, it derives central fields of action and political options.

[306] Original German title „Sektorkopplung – Untersuchungen und Überlegungen zur Entwicklung eines integrierten Energiesystems“

[307] Heat may be differentiated between low temperature heat (space heating, hot water) and process heat (higher temperatures, other infrastructure).

[308] Several other categorizations of "sectors" exist in the literature: related to the energy industry sectors are also "industry", "transport", "trade, commerce and services" and "private households".

The Federal Government's Climate Protection Plan (adopted in November 2016), distinguishes between "energy industry", "building sector", "mobility", "industry and commerce", "agriculture" and "land use and forestry" in order to define sector targets.

The study uses the REMod-D optimization model, which models expansion, replacement and renovation using assumptions about the respective cost for power plants, renewable energy, storage (electricity and heat), buildings, transport and power-to-X technologies. The model optimizes cumulative total cost over the period 2015-2050, under the constraint that GHG emission limits are strictly adhered to for each year.

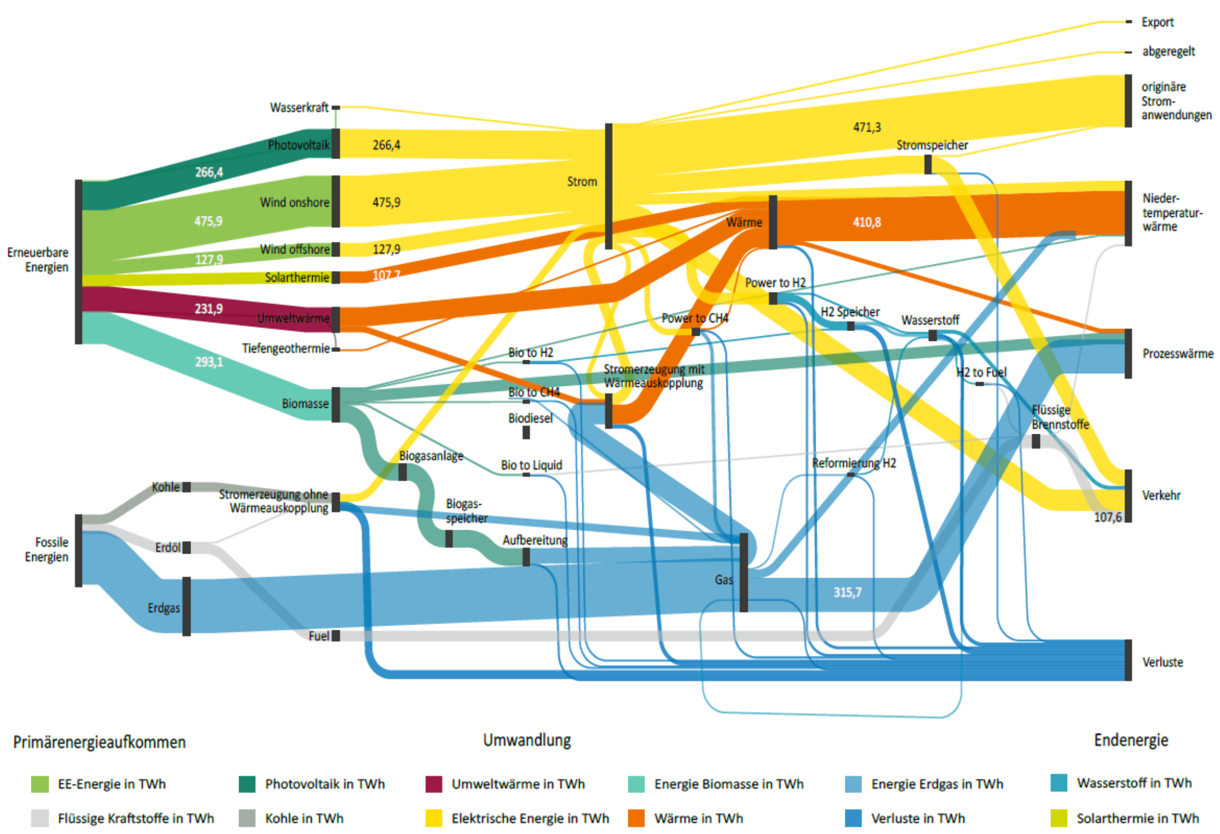
17.6.2.1.3 Scenarios

The study examines seven climate policy scenarios and one reference scenario. The reference scenario assumes a 40 percent reduction in energy-related CO_2 emissions by 2030 and no changes thereafter. The policy scenarios result from the combination of emissions reduction target scenarios and energy system scenarios. The target scenarios prescribe a reduction of GHG emissions by 60, 75, 85 or 90 percent for 2050, compared to 1990 levels. The energy system scenarios either prescribe a certain technological composition (e. g. hydrogen-based economy), or they are "open" (i. e. the technological composition is determined endogenously by the model).

17.6.2.1.4 Results

Figure 93 exemplifies a main result of the study, depicting the energy balance for the scenario "85_open". It shows the interconnections of the energy system from primary energy on the left to final energy consumption on the right. Every scenario features a different energy balance.

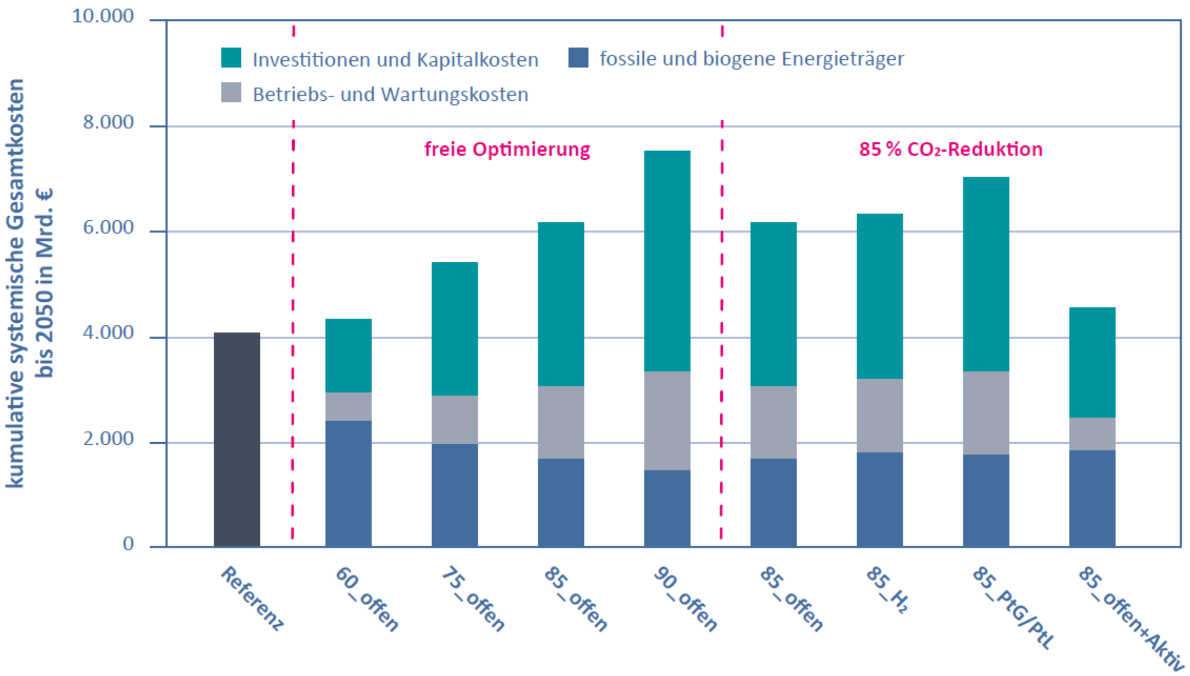
Figure 93: Example of sector coupling for scenario "85_open"



Source: Ausfelder et al., 2017 (Figure 32)

Figure 94 shows the cumulative energy system costs (2020-2050) for the reference scenario as well as the 7 climate policy scenarios. Costs increase with the ambition and an optimal technology mix (scenarios "open") decreases the overall costs. For more ambitious scenarios the cost for fossil and biogenic primary energy carriers (blue) are replaced by investment and maintenance costs of a more sustainable energy system (green). Note that the scenario "active" features low costs as it assumes — by intention optimistically —that significant reductions in consumption occur without entailing additional costs.

Figure 94: Sector coupling study: Cumulative energy system costs (2020-2050)



Source: Ausfelder et al., 2017 (Figure 35)

The total mitigation costs correspond to the difference between the respective policy scenarios and the reference scenario (see also Figure 100). Wider economic effects such as the creation of local added-value or employment effects are not taken into account in the cost estimate. Nor does the model consider the technological export opportunities entailed by a successful energy system transformation.

The study does not depict average costs (even though those could be easily derived from the presented results) nor marginal costs.

17.6.2.2 dena lead study integrated energy system transformation[309]

17.6.2.2.1 Aims

The aim of Bründlinger et al., 2018 is to identify realistic transformation paths for achieving the German climate targets from today's perspective and to determine their economic costs and the distribution of costs to end consumers. Specifically, it identifies solutions and framework conditions for an optimized, sustainable energy system by 2050 and analyses realistic options in four sectors with numerous sub-sectors. It thus primarily elaborates practical advice and recommendations to reach a certain climate target. The respective mitigation costs are calculated but are not the primary focus.

[309] Original Title in German „dena-Leitstudie Integrierte Energiewende"". dena is the German Energy Agency (Deutsche Energie Agentur).

17.6.2.2.2 Modelling approach

The study uses the model DIMENSION+, a partial analysis model of the German energy system which considers interactions with the EU energy market. The modelling focuses on minimizing the costs of the energy system (which are mainly primary energy consumption, plant investments and operation, infrastructure investments and operation).

As primary input this study uses exogenously given reduction targets in the form of annual quantity limits regarding the GHG emissions of the German overall system. The annual limits apply cumulatively across all sectors (buildings, industry, transport, energy). The allocation across sectors is determined within the model, but not entirely endogenous. Investment decisions for technologies in the final energy consumption sectors buildings, industry and transport are provided exogenously (i.e. they represent realistic paths from the point of view of the study's co-authors). They are thus not part of the model optimization routine. In this sense, the model is not a pure cost-efficiency model. The provision of energy, including dispatch and investment in the electricity system, is cost-optimal for each scenario. Finally, the technological progress until 2050 for various technologies (improved efficiency and reduced investment costs) is modelled using learning curves (for renewable energies, for technologies of the PtX value chains, for heating systems or vehicles). The resources (e. g. research funds, working time, etc.) that are necessary for technological progress are not considered.

The study does not carry out any macroeconomic analysis. Therefore, no statements can be made about e. g. economic growth, jobs, or the interest rate level.[310] Furthermore, it does not consider the business perspective, and thus taxes, subsidies, levies or other state interventions.

17.6.2.2.3 Scenarios

There are four climate policy scenarios and one reference scenario. The four climate policy scenarios arise from the combination of two targets scenarios and two energy system scenarios. The targets scenarios prescribe a reduction of GHG emissions by either 80 percent or by 95 percent (for 2050 compared to 1990 levels). The energy system scenarios are an electrification scenario and a technology mix scenario. The electrification scenario assumes a transformation of the energy system with rapid and extensive electrification of the final energy consumption sectors. The technology mix scenarios use a broader variation of technologies and energy sources in the final energy consumption sectors. For the 80 percent scenarios, CCS has been ruled out as a mitigation option. For the 95 percent scenarios, CCS has been partly and industry specific introduced to reach this target. In addition, these 95 percent scenarios assume more innovative production methods. The scenarios are labeled "Electrification 80 (EL80)", "Technology Mix 80 (TM80)", "Electrification 95 Innovation (EL95)" and "Technology Mix 95 Innovation (TM95)".

17.6.2.2.4 Results

The mitigation costs of different transformation paths (in the energy sector and in the energy-consuming sectors) are defined as the additional costs as compared to a non-target reference scenario. On this basis, the transformation paths can be evaluated and compared, but no statements can be made about the cost optimum of the overall system. The study did also estimate the investments in the industrial sector. As plants in the industrial sector are usually very specifically designed, investment costs are sector specific. The study also takes into account that some of the technologies involved are still to be developed or that their further development is uncertain.

[310] Additional investment in mitigation could, on the one hand, stimulate the economy and contribute to higher economic growth, On the other hand it could also slow down economic growth if capital is diverted in inefficient directions.

Figure 95 depicts the model's method to quantify mitigation costs (i.e., considered cost-types, sectors and allocation). The figure illustrates that the costs are modeled in considerable detail, down to sectoral level.

Figure 95: Dena national mitigation study: quantification of total costs and redistributions to final consumption sectors

Kostenart		Technologien	Gebäude Heizung, Dämmung	Industrie Power-to-Heat	Verkehr Fahrzeuge, nahe Infrastruktur	Stromerzeugung Kraftwerke (inkl. KWK), EE, Speicher	PtX-Erzeugung PtX-Anlagen	Infrastruktur Strom- und Gasnetze (F/ÜNB und VNB) und Weitere
direkte (primäre) Kosten	Kapitalkosten	Altinvestition	x	x*	x	x	-	✓
		Neuinvestition	✓	x*	✓**	✓	✓	✓
		Rückbau	x*	x*	x*	x*	-	■
	Betriebskosten/ Instandhaltung	Altinvestition	✓	✓	✓**	✓	-	✓
		Neuinvestition	✓	✓	✓**	✓	✓	✓
	Brennstoffkosten	Mineralöl, Gas, Kohle, Uran, Bioenergie	✓	✓	✓	✓	-	-
Kostenumverteilung (sekundäre Kosten)	Strombezug	heimisch	✓	✓	✓	-	✓	-
		importiert	✓	✓	✓	-	✓	-
	PtX	heimisch	✓	✓	✓	✓	-	-
		importiert	✓	✓	✓	✓		-
	Infrastruktur	Strom	✓	■	■	-	x	-
		Gas	✓	■	■	✓	x	-
		weitere	✓	■	■	-	x	-
neutrale Kosten	CO_2-Zertifikate bzw. -Steuer		✓	✓	✓	✓	-	-

✓ betrachtet, ■ teilweise betrachtet, x nicht betrachtet, - nicht relevant

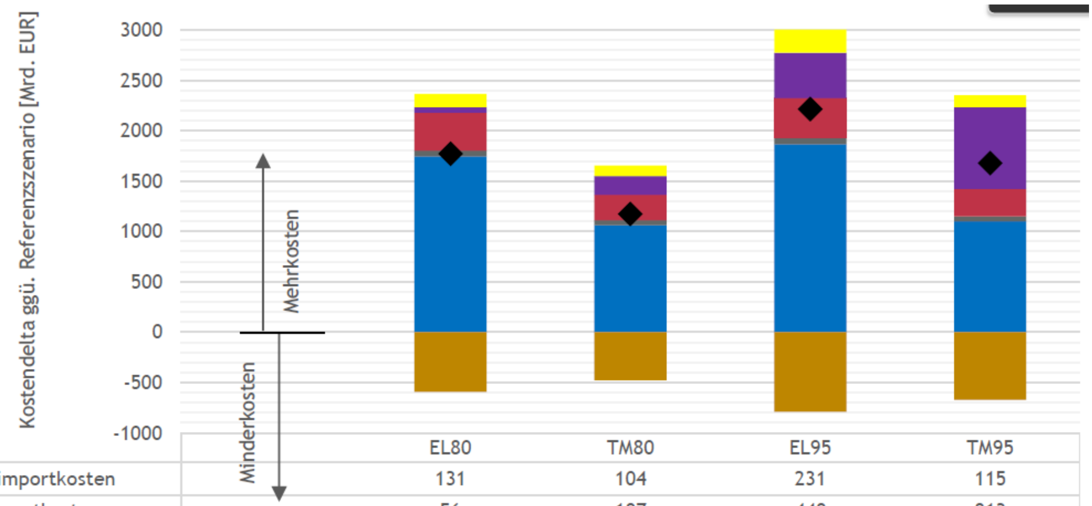
*Kosten können aufgrund sehr unsicherer Datengrundlage nicht oder nicht belastbar quantifiziert werden. **Nicht enthalten sind Schienenverkehr, Schifffahrt und Luftfahrt.

Source: Bründlinger et al., 2018 (Figure 10)

Figure 96 shows the overall and annual mitigation efforts as well as mitigation costs of the four scenarios in comparison to the reference. The mitigation costs are defined as the total cumulative energy system cost over the period 2018–2050. Costs are higher for the 95 percent scenarios and for the scenarios that assume intense electrification, primarily because investment costs are higher in those cases. Note that the additional costs for the EL80 scenario are roughly equal to the costs of TM95. These findings illustrate the crucial role of the overall design of the energy system transformation.

Figure 96: Dena national mitigation study: Emission reductions and additional cumulative energy system costs (2018-2050) as compared to reference scenario

Entwicklungen bis 2050 (Auswahl)	Referenz	80 %-Klimazielszenarien		95 %-Klimazielszenarien	
		Elektrifizierung (EL80)	Technologiemix (TM80)	Elektrifizierung (EL95)	Technologiemix (TM95)
THG-Emissionen	Gesamt				
	470 Mio. t CO_2ä (- 62 % ggü. 1990)	250 Mio. t CO_2ä (-80 % ggü. 1990)	250 Mio. t CO_2ä (-80 % ggü. 1990)	64 Mio. t CO_2ä (-95 % ggü. 1990)	64 Mio. t CO_2ä (-95 % ggü. 1990)
	Durchschnittliche jährliche Minderung ab 2015				
	13 Mio. t CO_2ä	19 Mio. t CO_2ä	19 Mio. t CO_2ä	24 Mio. t CO_2ä	24 Mio. t CO_2ä



	EL80	TM80	EL95	TM95
Stromimportkosten	131	104	231	115
PtX-Importkosten	56	187	448	813
Primäre Brennstoffkosten	-592	-480	-790	-671
Infrastrukturkosten	377	253	391	272
FOM-Kosten**	54	47	68	52
Kapitalkosten*	1.746	1.064	1.866	1.098
◆ Summe	1.772	1.175	2.215	1.679

*Kapitalkosten für Kraftwerke, PtX-Anlagen, EE-Anlagen, Gebäudedämmung, Heizungen, Fahrzeuge und nahe Verkehrsinfrastruktur (Ladesäulen, etc.) sowie CCS jeweils Zubau ab 2018.

**FOM-Kosten: Fixe Betriebs- und Wartungskosten der in * genannten neuzugebauten und bestehenden Anlagen.

Source: Bründlinger et al., 2018 (Table 1 and Figure 128)

Again, this study does not depict average costs (even though those could be easily derived from the presented results), nor marginal costs.

17.6.2.3 Climate Paths for Germany[311]

17.6.2.3.1 Aims

Gerbert et al., 2018 aims to model economically cost-efficient climate paths for Germany until 2050, using a detailed description of five sectors: industry, transport, households & commerce, energy conversion, and land & waste management. In addition, it identifies political fields of action and describes the additional investments that are necessary to achieve the climate targets. It shows that there are also export opportunities due to a growing international market for climate protection technologies. Finally, there is a qualitative discussion of measures that do not currently have technological or economic maturity, but may contribute significantly to emission reductions when, or if, maturity is reached ("game changer").

17.6.2.3.2 Modelling approach

Mitigation measures are prioritized according to mitigation costs, taking into account limits due to reinvestment cycles, ramp-up times or the expansion potential of renewable energies. Additionally, several barriers hinder or slow down the deployment of measures (a delay in nuclear phase-out, land-use trade-offs, acceptance of demand-side measures, acceptance of CCS, or reductions in livestock as the last possible measure). Only technologies that are considered sufficiently certain to be ready for use — from today's perspective — and whose effects can be quantified by 2050, are used.

The study shows "additional" economic costs. These comprise all costs for unprofitable measures that are already carried out in the reference scenario. In addition, they comprise all

[311] Original Title in German „Klimapfade für Deutschland"

additional costs of the policy scenario as compared to the reference. To calculate the mitigation costs, (1) additional investments are annualized with an interest rate of 2 percent over the lifetime of the measure, (2) energy savings are deducted and (3) costs for new energy sources (mainly synthetic fuels) are added. The model does not include the costs of R&D or the cost of restructuring.

Sectoral energy demand and the electricity market are simulated with individual, bottom-up energy industry models that determine sectoral final energy consumption by energy source and application. These bottom-up models are coupled with the model VIEW via an input-output model. VIEW models the global economy and contains interactions and feedbacks between the individual countries. It is used for the quantitative calculation of the scenarios and the determination of the wider economic effects on GDP.

17.6.2.3.3 Scenarios

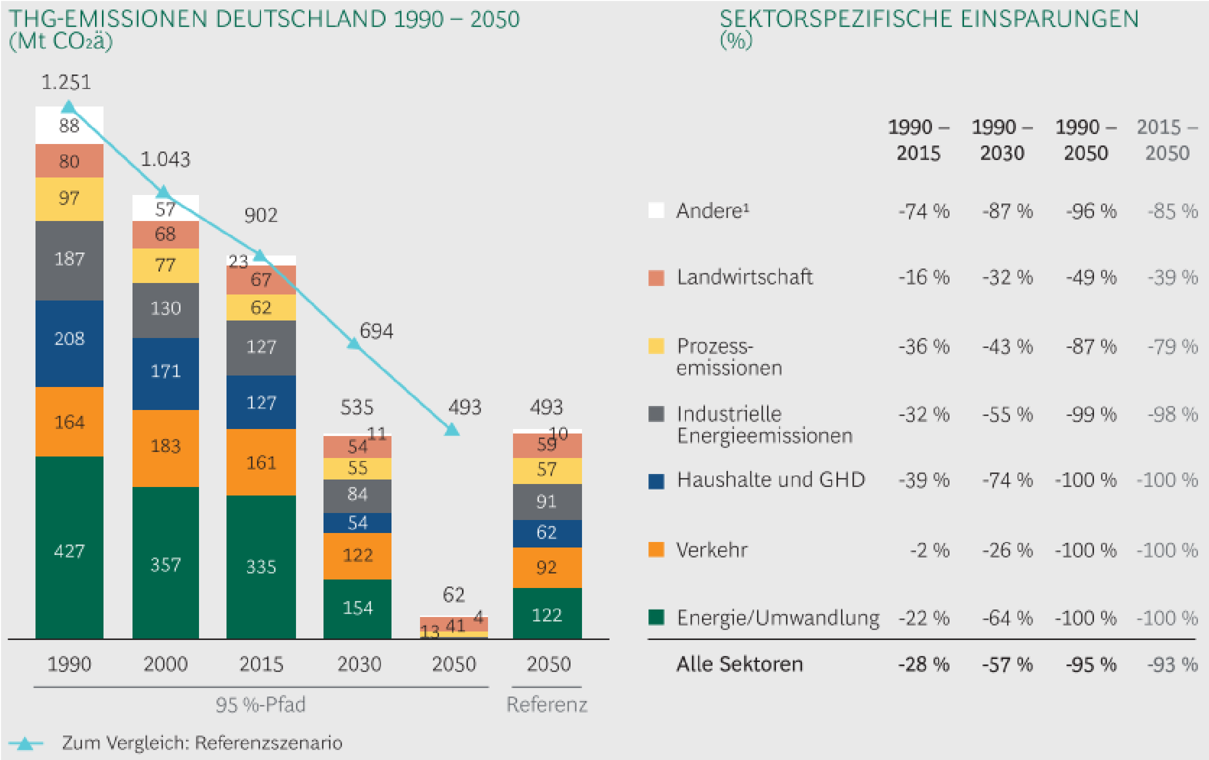
There are again four climate policy scenarios and one reference scenario. The four climate policy scenarios result from the combination of two targets scenarios and two scenarios regarding national vs. global action. The targets scenarios prescribe a reduction of GHG emissions by either 80 percent or by 95 percent (for 2050 compared to 1990 levels). In the national effort scenarios ("Nationale Alleingänge"), nations have investment and modernization programs, which are however uncoordinated. In the globally effort scenarios ("Globaler Klimaschutz"), climate mitigation is globally coordinated such that there is a significantly growing world market for climate technologies (especially in the 95 percent reduction scenario). These two scenarios differ mainly because of the price of fossil fuels (which are lower in the global effort scenario, due to lower demand).

The scenarios describe consistent bundles of technical measures. They thus implicitly assume cost-efficiency. Inefficient policy design (e.g. a delay in grid expansion) would increase the mitigation costs.

17.6.2.3.4 Results

Figure 97 shows the greenhouse gas emissions of various sectors for the 95% reduction path and reductions as compared to the reference. In 2050, most sectors are essentially emission-free; only industry processes and agriculture remain as major emitters. Especially the agricultural sector, which contributes to two thirds of the remining emissions — half of which stem from cattle farming.

Figure 97: Greenhouse gas emissions of various sector for the 95% reduction path (left) and reductions as compared to reference (right)



Source: Gerbert et al., 2018 (Figure 13)

Figure 98 depicts mitigation costs for achieving the 80% and 95% path as compared to the reference case, respectively. The x-axis shows the contribution of the various measures as determined by the study. The y-axis are the respective mitigation costs. The following points lists the assumptions regarding the mitigation costs:

- They are average cost (cumulative costs and cumulative emissions reductions).
- They are net costs. That is, additional investment costs subtracted by reduced operating costs (i. e. costs of fossil fuels).
- They are cumulative from 2015–2050 and discounted to 2015 with a rate of 2%.
- Emissions reductions are as compared to the reference scenario, which already contains some mitigation policies. Wind energy, for example, is already being strongly expanded in the reference, such that wind does contribute little additional emission reduction (at least in the 80% path).
- Average mitigation costs take into account the costs along the transformation path (that is they do take into account the state of the learning curve at any given point in time). This is especially relevant for technologies that exhibit a strong dynamic over time (e.g. a strong learning effect).
- Investments in equipment and infrastructure are taken into account across sectors and annualized over the lifetime of the asset. For example, additional to the investments in more

expensive electrical cars, the required charging infrastructures and the distribution network infrastructures in the electricity system are considered.

- Attribution of a measure are along the total value chain. That is, beside emissions at the source also emissions for the production of electricity or district heating are taken into account (e. g., if the installation of more efficient lighting reduces electricity consumption, the GHG emissions saved in the transformation sector are attributed to this measure). To allocate the reduction to individual overlapping measures, the following sequence is used: 1. efficiency, 2. GHG emission reduction of electricity and district heating production, and 3. substitution of energy sources.[312]
- The electricity costs are the same for all users and include all costs (i.e. costs of the entire renewable energy park, the grid infrastructure at all grid levels, the flexible backup capacity, fuel costs and the capital costs of displaced power plants that had not yet reached the end of their technical life).
- Costs are from a macroeconomic perspective. The business perspective differs, as the study does not consider taxes, subsidies or customs duties and energy prices.

Some measures have negative costs. Those are not already implemented either because there are not beneficial from a business perspective or additional barriers exist, that are not monetized.

The most expensive measures for the 80% climate path have mitigation costs of 100–135 € / tCO_2 and stem from the transport sector. The 95% path includes additional measures that have not been part of the 80% path either because of their higher costs or because they have been deemed socially inacceptable in the 80% path (primarily carbon capture and storage). This explains the — at first glance puzzling — results that several additional measures from the 95% path are cheaper than those from the 80% path. To reach the 95% reduction target, several rather expensive measures have to been implemented such that the most expensive ones reach 400 €/tCO_2. This illustrates the problem that the "last percentages" are disproportionally expensive.

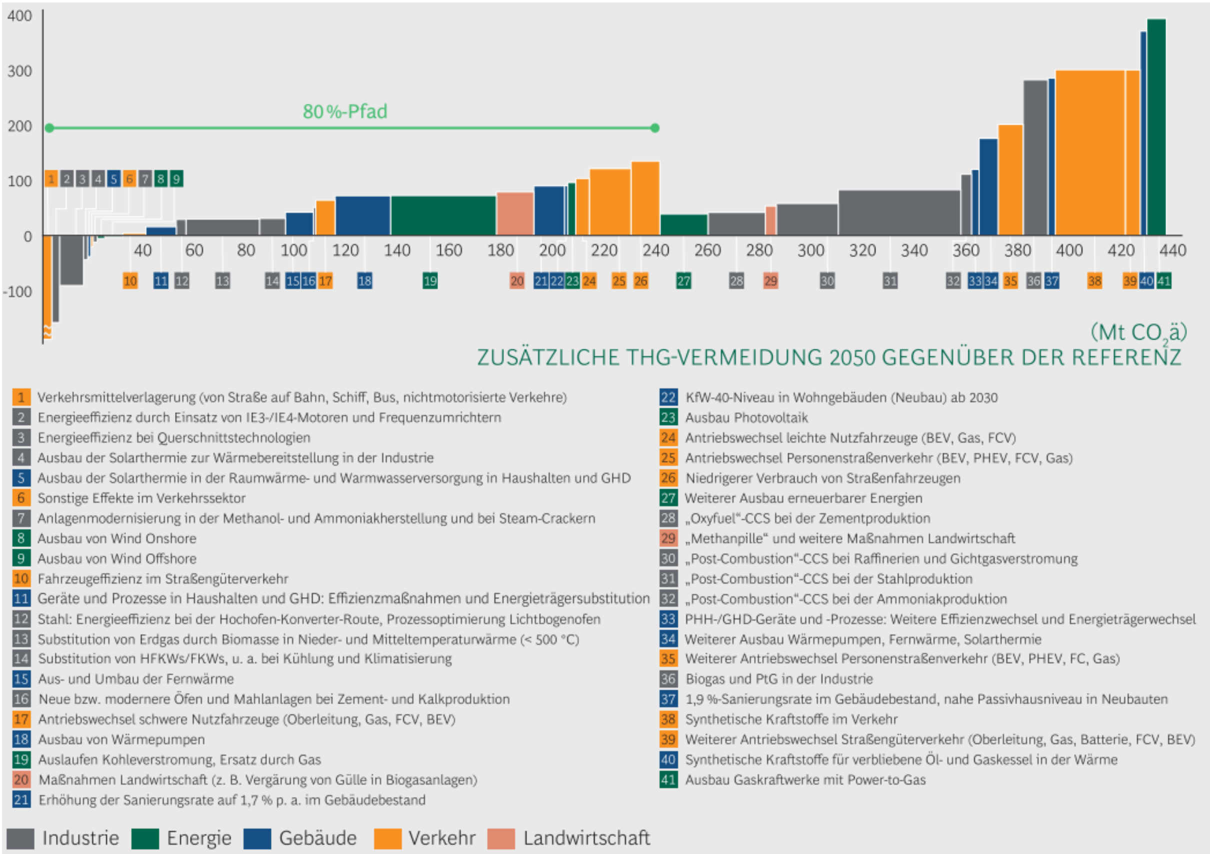
[312] An example from the study illustrates this mechanism:

1. More efficient lighting saves electricity in a given year. The associated GHG savings are calculated using the emission factor of the electricity system at the beginning of the year.

2. In the same year, an expansion of photovoltaics takes place, which also saves GHG emissions in the electricity system. These savings are calculated on the (now lower) electricity production after taking into account all efficiency measures.

3. In the same year, a combustion engine is replaced by a battery-powered car. This saves GHG emissions from the combustion of fossil fuels, but generates new GHG emissions in the electricity system. These new GHG emissions are calculated using the emission factor of the electricity system at the end of the year.

Figure 98: Average mitigation costs as compared to reference for the 95% path (in €/t CO_2eq)



Legend: Cumulative costs 2015-2050 discounted to 2015 (for definition of costs see text).
Source: Gerbert et al., 2018 (Figure 18)

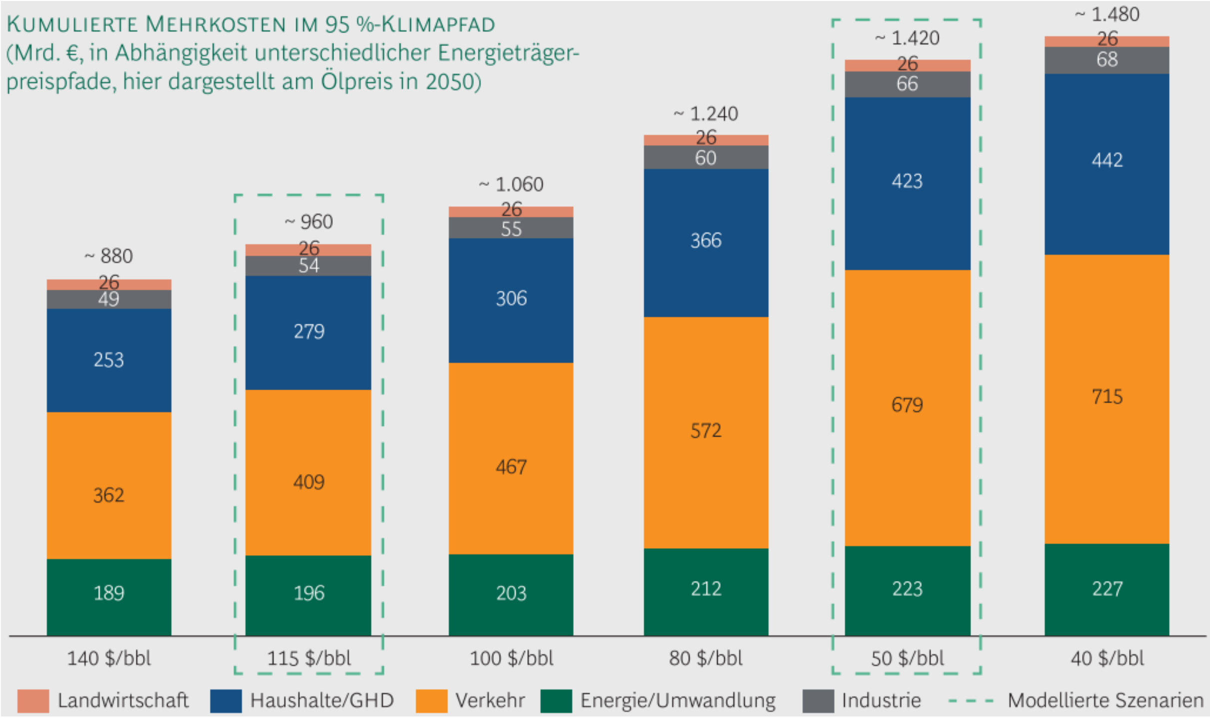
Figure 99 shows the cumulative additional costs in the 95 % climate path and the contribution from different sectors. The headline number used in the study for the 95% path are 960 billion € (for the 80% path the headline costs are 470 billion €; not shown). The authors of the study caution that these results are uncertain. Specifically, they note that the costs are to be understood as best-guess with respect to future technology costs (e. g. learning curves) and that it has been assumed that measures are implemented optimally. Technological costs are often overestimated and thus cost estimates may be too high. Inefficient policies, on the other hand, may increase the costs.

The figure also shows the strong influence of the fossil energy price scenario (shown as a proxy are the oil prices in 2050).[313] Lower fossil energy prices translate into higher mitigation costs (as this lowers the energy costs in the baseline). However, lower future fossil energy prices may be causally triggered by lower demand of the global effort scenario. The corresponding decrease of the energy bill (and decreasing investments in extraction of fossil energy carriers) may be attributed as benefit and thus lowers the mitigation costs. In this case the study's additional mitigation cost for the 95% path are 380 billion € (and for the 80% path mitigation costs are –270 billion €, i.e. mitigation is overall beneficial).[314]

[313] The national effort scenarios correspond to an oil price in 2050 of 115 $/bbl; the globally effort scenario to 50 $/bbl.

[314] Unfortunately, the study does not provide details of that calculations or its underlying methodology.

Figure 99: Cumulative additional costs in the 95 % climate path (billion €), depending on different energy carrier price paths (shown here as the oil price in 2050)



Legend: Cumulative costs 2015-2050 discounted to 2015 (for definition of costs see text).
Source: Gerbert et al., 2018 (Figure 18)

The study also considers wider macroeconomic effects on the GDP. There are several opposing effects: On the positive side, GDP increases as the additional expenditure on investments increases demand, revenue and income in several sectors. There may also be a so-called "multiplier effect", as the additional incomes is in turn used by private households for saving and private consumption, such that the increase in aggregate income can be greater than the original additional expenditure. In addition, the mitigation measures also lower spending on energy carrier imports, which increases domestic income.

There are also negative effects on GDP. Additional investments increase production costs for businesses and in turn lower international competitiveness thereby depressing export. Other types of investment may be "crowed out". Private consumption may decrease due to higher credit costs. Finally, the higher electricity prices reduce the income of households and industry.

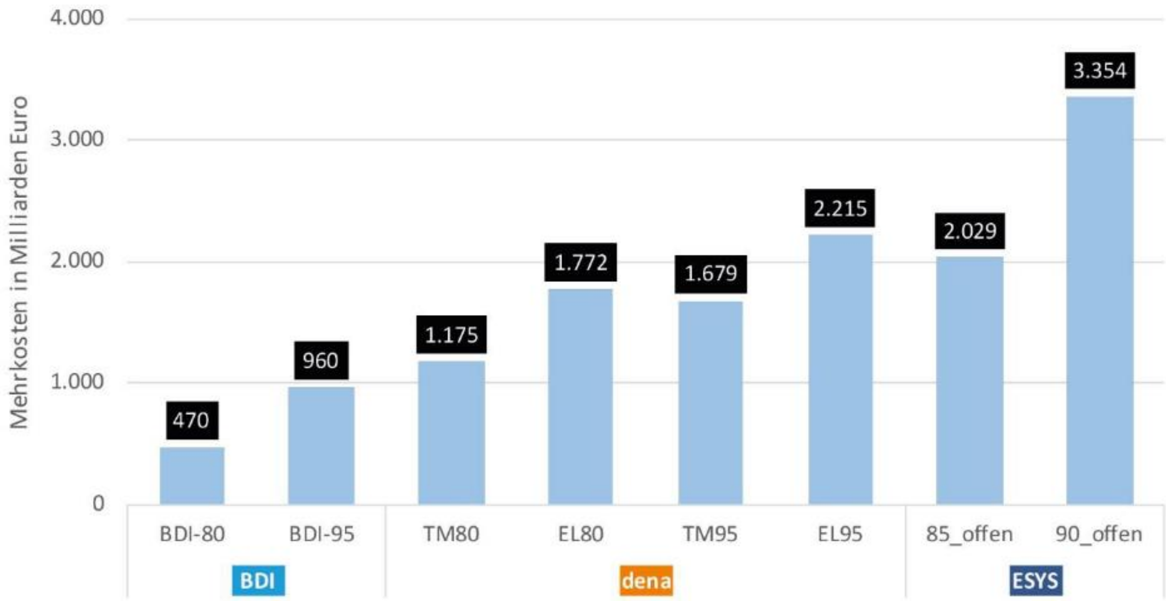
Modelling these macroeconomic effects and their interactions with the input-output model VIEW, shows a GDP increase of 0.4 to 0.9 percent in 2050 across all scenarios considered. The study thus concludes that in macroeconomic terms climate mitigation is neutral or slightly positive, even without considering the prevented climate damages.

17.6.2.4 Comparison of the previous three studies

The three studies presented in the previous chapters all focus on climate mitigation in Germany. Their focus is on presenting cost-efficient ways to reduce emissions in all effected sectors in a coordinated approach. For that purpose, those sectors and their technological options are presented and modelled in detail.[315] As additional information, the ensuing mitigation costs are presented.

All studies present total cumulative costs up until 2050 for several scenarios (apart from using several scenarios, they are all deterministic). Figure 100 shows that the spread of the models is considerable (470 to 3'354 billion Euro). The reasons are different assumptions on the influencing factors such as autonomous efficiency gains in the baseline, costs for energy imports, technology costs, considered sectors and greenhouse gases (e. g. methane and nitrous oxide from agriculture) or interest rates. The ESYS study in addition assumes that power-to-X synthetic fuels are not imported but only produced in Germany. This increases energy autarky but also mitigation costs.

Figure 100: Selected results of three national mitigation cost models (additional costs in billion Euro till 2050 compared to the baseline scenarios of the respective study)



Source: Stephanos et al., 2019

17.6.2.5 Paths for the energy transformation[316]

17.6.2.5.1 Aims

Robinius et al., 2019 scrutinize on how to design a consistent and cost-efficient CO_2-reduction strategy to meet national GHG reduction targets.

17.6.2.5.2 Modelling approach

The study uses a model suit developed at the research center Jülich. It includes the national energy supply across all sectors (households, energy sector, industry, transport), such that it can calculate cost-optimal transformation strategies, considering a variety of reduction measures that compete with each other across all sectors. A special feature of the model is for example that it analyses the techno-economic generation potentials of wind and solar with very high spatial resolution, using weather data from 37 years. The model does only consider CO_2 (but no other GHG).

[315] Technological options relate to e. g. PV, wind and other power plants (adjustable vs. band load), power-to-X (synthetic energy carriers), the technology mix in the transport sector, retrofit of buildings or energy efficiency of the industry.

[316] Original Title in German „Wege für die Energiewende".

17.6.2.5.3 Scenarios

There are two targets scenarios prescribing a reduction of GHG emissions by either 80 percent or by 95 percent (for 2050 compared to 1990 levels). The scenarios do not include any further technology targets (such as shares of renewables). They do include carbon capture but only allow for its utilization (CCU is possible) but not its storage (CCS is not possible).

17.6.2.5.4 Results

Figure 101 compares several mitigation costs types for the two scenarios. The cumulative costs are in the range as given by the previous three studies (see Figure 100). In addition, Robinius et al., 2019 explicitly presents average and marginal mitigation costs, which could in principle also be calculated for the other three studies but are not presented there.

Figure 101: Several mitigation costs types of Robinius et al., 2019

Jahr 2050		80 SZENARIO 80	95 SZENARIO 95
Mehrinvestitionen ggü. heute	Mrd. €/Jahr	102	192
Eingesparte Energiekosten ggü. heute	Mrd. €/Jahr	53	64
Saldierte Kosten	Mrd. €/Jahr	49	128
Anteil der saldierten Kosten am BIP 2050	%	1,1	2,8
Durchschnittliche Vermeidungskosten	€/t CO_2	83	170
Grenzvermeidungskosten	€/t CO_2	306	744
Kumulierte Mehrkosten heute-2050	**Mrd. €**	**655**	**1.850**

Tabelle 1: Ausgewählte Kosten der jeweiligen Szenarien

Source: Robinius et al., 2019

Note that this study does not model non-CO2 GHG, such that the presented costs underestimate the mitigation costs — at least for the 95% scenario. Considering all GHG, CO_2 has to be reduced by more than 95% to reach the overall target, as non-CO_2 emissions from e. g. agriculture are especial hard and costly to reduce by 95% (see the study “Climate Paths for Germany” which finds that two thirds of the remaining GHG in 2050 stem from agriculture).[317]

[317] For less ambitious reduction target including non-CO_2 may decrease costs are there exist some low- cost non-CO_2 mitigation options (such as destruction of industrial process gases (e.g. N_2O) or replacement of CFCs or HCFCs).

17.6.3 A Study focusing on the UK

17.6.3.1 "What are the key drivers of MAC curves? A partial-equilibrium modelling approach for the UK" (Kesicki, 2013)

17.6.3.1.1 Research Question

The journal article from Kesicki assesses which factors influence an economy-wide Marginal Abatement Cost (MAC) curve and how sensitive the MAC curve is by using a bottom-up model for the UK for 2030 (Kesicki, 2013).

17.6.3.1.2 Approach

In this study, Kesicki used UK MARKAL which is a partial equilibrium model rich in technological detail. It is a dynamic linear programming energy system optimization model. The objective function maximises producer and consumer surplus. It covers CO_2 emissions only and assumes perfect foresight.

To assess the sensitivity of the Marginal Abatement Cost curves with respect to a a set of different factors, Kesicki conducts a sensitivity analysis of the model based on a variety of scenarios (see below). To generate the MAC curves for each scenario, 46 model runs with the same underlying scenario-input assumptions are performed, applying different model-wide CO2 tax levels leading to different emission levels. Focus is on the MAC for the UK and the year 2030.

17.6.3.1.3 Scenarios and core assumptions

Kesicki compared 16 scenarios grouped into six categories of potential influencing factors. These are outlined in Table 36 below.

Table 36: Overview of scenarios in Kesicki (2013).

Scenario	Category	Description
REF	*Reference case*	Carbon tax increase by 5% p.a. from 2010
ZERO-BEFORE	*Path dependency*	Carbon tax is zero before 2030
CONST-AFTER	*Path dependency*	Carbon tax is constant after 2030
INCR-AFTER	*Path dependency*	Carbon tax increases with 10% p.a. from 2030
ZERO-AFTER	*Path dependency*	Carbon tax is zero after 2030
HIGH-BEFORE	*Path dependency*	Carbon tax is kept constant on the 2030 level from the BASE scenario for the period 2015-2030
PDR10	*Discount rate*	Hurdle rates introduced for all technologies at 10%, previously existing rates were doubled
SDR	*Discount rate*	Discount rate lowered to 3.5%, all hurdle rates, taxes and subsidies removed
FF+	*Fossil fuel price*	Costs for coal, coking coal, oil, refined products and natural gas increased by 100%

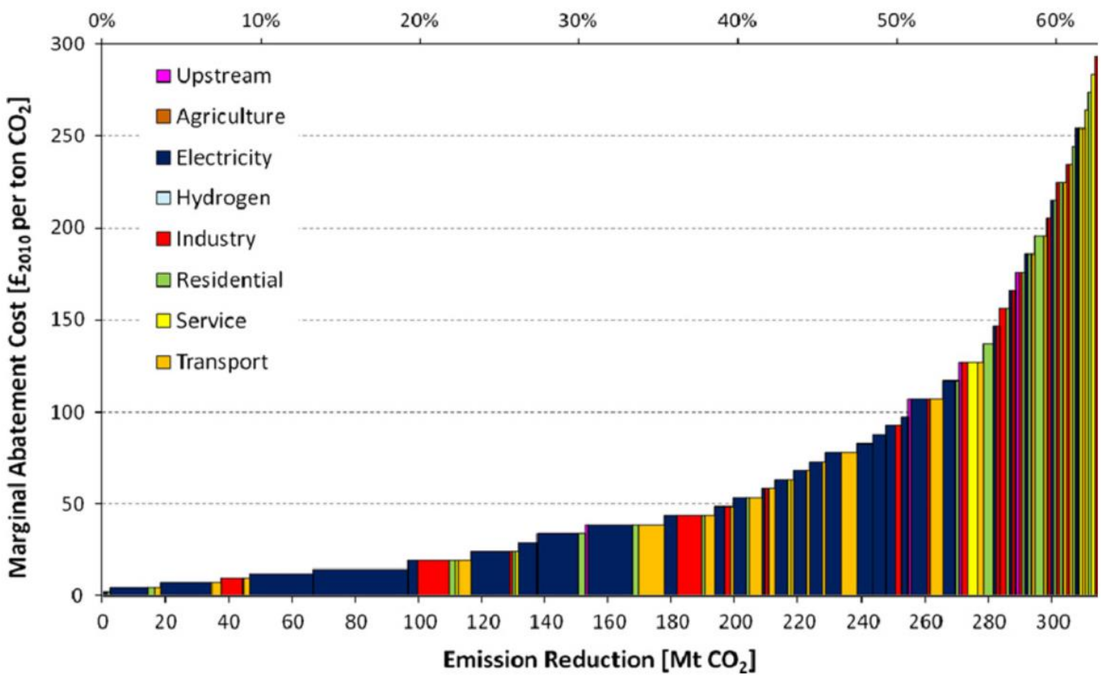
FF++	*Fossil fuel price*	Costs for coal, coking coal, oil, refined products and natural gas increased by 200%
GAS	*Fossil fuel price*	Costs for natural gas decreased by 50%
NO-NUC-CCS	*Technology issues*	No investments are allowed into nuclear power plants and CCS technologies
NO-BIOMASS	*Technology issues*	No biomass/biofuel imports allowed; domestic biomass production reduced by 50%
IEP	*Technology issues*	Investment costs increased by 200% for all CCS technologies, biomass, nuclear, tidal, wind, wave
DEM+	*Demand level*	All energy service demands increased by 20%
DEM-	*Demand level*	All energy service demands decreased by 20%

Source: Table 1 from Kesicki (2013).[318]

The reference scenario uses the standard assumptions of the MARKAL model, with the CO_2 tax increasing over time from 2010 to 2050 and applying the model-inherent discount rate of 5% annually (Kesicki, 2013).

17.6.3.1.4 Results

Figure 102: Marginal Abatement Cost Curve for the UK for 2030



Note that the height of the bars represents the marginal abatement costs, the width of the bars reflects the amount of abated emissions.
Source: Figure 1 from Kesicki (2013) [319]

[318] Permission was obtained under the licence number 5012561227665.

[319] Permission was obtained under the licence number 5012561227665.

The figure above (Figure 103) taken from Kesicki (2013) depicts the Marginal Abatement Cost Curve for the UK for 2030 for the reference scenario, differentiating between sectors.

In summary, the Kesicki study finds that the MAC curve is sensitive regarding assumptions on discount rates, the availability of key mitigation technologies and the assumed demand level. Changes in fossil fuel prices did not show a strong effect. With regard to path dependency, the sensitivity analysis finds that the static snapshot of the 2030 MAC curve from MARKAL was not very sensitive with regard to changes in assumption on CO2 tax trajectories before 2030 or after 2030. Kesicki summarises the findings in Table 37. Figure 103 shows the results of the sensitivity analysis in more detail.

Table 37: Influence of the change in different factors on MAC curve found in Kesicki (2013):

Category	Influence
Path dependency	-
Discount rate	+
Fossil fuel price	-
Technological issues	o/+
Demand level	+

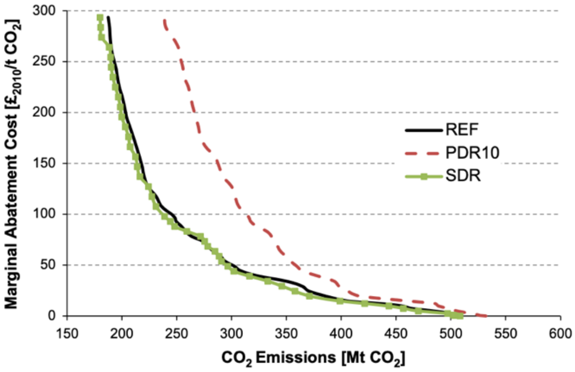
Note: (+) strong influence found, (o) medium influence, (-) weak influence

Source: Table 5 from Kesicki (2013) [320]

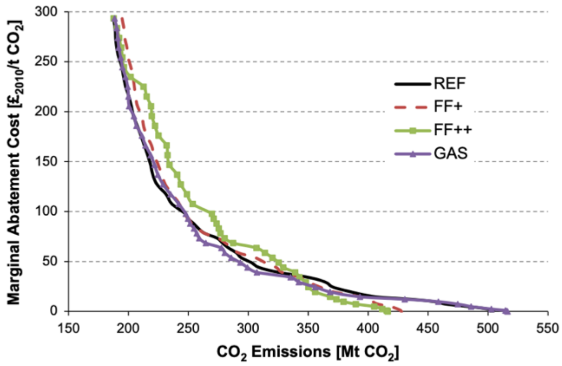
[320] Permission was obtained under the licence number 5012561227665.

Figure 103: Sensitivity Analysis of MAC curves for different discount rate scenarios

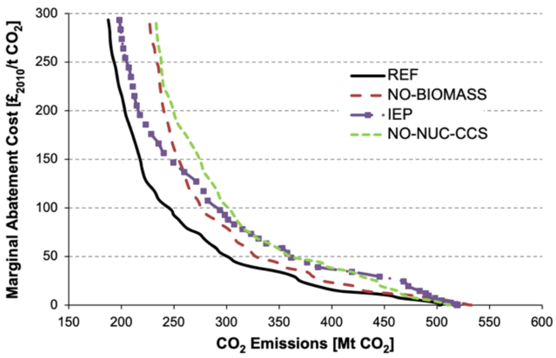
a) MAC curve for different discount rate scenarios



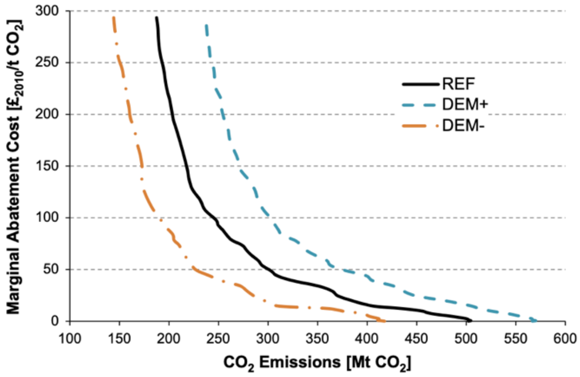
b) MAC curve for different fossil fuel price scenarios



c) MAC curve for different technology scenarios



d) MAC curve for different demand scenarios



Note: In Figure a) "REF" assumes a discount rate of 5%, "SDR" assumes a social discount rate of 3.5% and "PDR" assumes a high private discount rate of 10%. Moreover, assumptions on technology hurdles differ.
Source: Figures 5,6,7,8 from Kesicki (2013) [321]

[321] Permission was obtained under the licence number 5012561227665.

18 Main findings for the mitigation cost perspective

The literature on mitigation costs is very diverse and reports large ranges in mitigation cost estimates. Apart from the multitude of differences in modelling approaches (which will be discussed below), there is also a range of different **mitigation cost metrics** reflecting different concepts of mitigation costs which are not directly comparable (see section 17.4.2).

- Looking for a similar concept to the Social Costs of Carbon on the damage cost side, **marginal abatement costs** (MAC) represent the costs of an incremental reduction in emissions by one unit. Many models report the *carbon price*[322] that results from imposing an emission constraint (e.g. carbon budget). As such, it reflects the additional costs that businesses or public investors would need to factor in for investment decisions, if a price-based policy instrument (carbon tax or emission trading) in line with the mitigation target was implemented. Limitations of the carbon price cost metric are that it - by definition - focuses on the cost of the last and thus most expensive unit of avoided emissions and by itself does not provide insights on the total (or average) costs of achieving the defined mitigation level. As a consequence, the carbon price is typically observed as increasing steeply for more ambitious mitigation efforts requiring, for example, complete decarbonisation and thus the deployment of costly mitigation technologies, although the difference in average abatement costs may be less pronounced. Moreover, if the carbon price is not the only policy instrument, the resulting carbon price level may not reflect the 'true' marginal costs of abatement. For example, if an effective energy efficiency policy or innovation policy is in place or assumed to be introduced in parallel, the required carbon price to achieve the same emission reduction target will be lower, as part of the emission reductions are achieved through the other policy, with the carbon price underestimating the full marginal costs. Thus, carbon prices only measure marginal abatement costs under idealised and simplified assumptions.
- As a consequence, studies assessing mitigation costs often use other cost metrics for providing information for (total or average) **policy costs** such as change in consumption, change in Gross Domestic Product (GDP), additional total energy system costs or (additional) investment costs compared to a baseline scenario. Yet, these cost metrics also have their individual limitations[323] and also partly depend on the model type, complicating cross model comparisons. The Area under the Marginal Abatement Cost Curve is also a common metric for policy costs, using information on marginal costs at different levels of mitigation for approximating total costs under the limitations stated above for MAC.

On the methodological side, there is a multitude of different models and approaches assessing long-term transformation pathways and the resulting costs for given mitigation targets (Cost-Effectiveness-perspective). Generally, a **higher level of detail and complexity comes at the**

[322] Typically, the term carbon price is used despite referring to all GHG emissions. An alternative term is 'emissions price' or 'shadow price of emissions'.

[323] For example, additional total energy system costs solely focus on the mitigation cost for the energy sector disregarding other sectors. GDP or consumption change reported by models covering the whole economy build on the questionable assumptions that i) GDP and consumption are suitable concepts to measure welfare, ii) GDP and consumption pathways could be adequately projected decades ahead – for the baseline and the policy scenario – and iii) feedback effects of climate impacts affecting GDP or consumption are disregarded. Moreover, for optimization models, deviations from the baseline per definition lead to consumption or GDP losses.

expense of the need for simplification in other regards. Broadly, **two main perspectives** can be differentiated**:**

- **Top-down perspective:** focus on the representation of economy-wide aspects at the expense of a lack of detail (typically General Equilibrium models)
- **Bottom-up perspective:** emphasis on the detailed technological representation of certain sectors from the engineering perspective, at the expense of 'missing the big picture' (typically Partial Equilibrium models)

Complex mitigation cost models **typically consist of a combination of different sub-models** that are either soft linked or hard linked (see section 16.2.2.3). This allows models to bring together aspects from the top-down and bottom-up perspective (so-called hybrid models), though typically one perspective dominates.

Another dimension for model complexity is the **regional coverage**. The majority of models used in the literature for analysing long-term mitigation pathways and assessing underlying drivers systematically, e.g., in model inter-comparison projects or the IPCC Assessment Reports, are **global mitigation models.**[324] These mitigation cost models aim to provide the 'big picture' for the global problem of climate change mitigation and decarbonisation interlinkages between regions. Yet, due to their global coverage these models typically only allow a coarse temporal and spatial disaggregation, e.g., disregarding heterogeneity by aggregating diverse countries into a limited number of model regions and working with larger time steps (e.g. 5 or 10 years).

This coarse disaggregation of global models is often criticised for its limitations in representing real-world complexity and socio-political aspects. **EU or Germany-level models** (see section 17.6) allow representing country characteristics and differences in detail (e.g., grid connections and cost differences) and partly include a temporal disaggregation at the level of hourly time slices allowing for analysing implications for energy system stability when supply of variable renewable energy sources is growing. However, they are less suitable for providing the 'big picture' of global interlinkages of decarbonisation. Moreover, also the group of regional or country-level models is large and very diverse, with models taking top-down or bottom-up perspectives. While the scientific community working on global mitigation cost models has made some efforts in defining harmonised input assumptions to allow better comparability between models (e.g., in model inter-comparison projects), there are less systematic (meta-)analyses of mitigation cost drivers on the regional level. We thus synthesise insights from both global and EU-specific mitigation cost literature to improve the understanding of which factors drive mitigation costs.

Mitigation cost estimates vary widely due to differences in underlying assumptions. These assumptions can be **model specific factors that characterise a specific model** or alternatively **variant factors that vary between model runs**. These elements both have normative (policy prescriptive) components and elements characterised by scientific uncertainty and technical limitations.

[324] The literature often refers to such models as so-called "Cost-Effectiveness-Integrated Assessment Models" (CE-IAMs) (also called detailed process IAMs). As the term IAM is also used for other very different types of models (see section 16.2.2.3.3) and not all relevant models would describe themselves as CE-IAMs, we refer to models used for mitigation cost assessment as 'mitigation models'.

Variant-factors depend on the specific model run and can at least to some degree be harmonized across models to allow better inter-comparison of results. These can be differentiated into

- ***Scenario assumptions***
- ***Normative choices*** with regard to parameter choice and implementation details.

The most relevant **scenario assumptions** are

- ***Socio-economic narratives*** (see section 17.4.3.1), for example in the form of Shared Socio-economic Pathways (SSPs), are storylines outlining assumptions on (potential) socio-economic developments. Socio-economic storylines such as the SSP scenarios define common assumptions about GDP and population growth, but also include underlying assumptions about lifestyles and 'ease' of technology diffusion. How these general storylines are implemented in specific models partly depends on the model set-up and is also partly at the discretion of the modeler. Unsurprisingly, SSP scenarios with higher mitigation challenges (e.g. increasing energy demand, regional rivalry, favorable conditions for fossil technologies) lead to higher mitigation costs or even infeasibility issues for ambitious mitigation targets, while socio-economic storylines assuming favorable conditions for mitigation (e.g. sustainable lifestyles, global cooperation, technology diffusion) are associated with lower mitigation costs. Ideally, results for different socio-economic storylines are presented allowing 'what-if' analysis of different possible developments. However, to reduce the number of pathways to compare with regard to other drivers, some studies choose to assess only selected SSP scenarios (frequently SSP 2- 'middle of the road'). This induces a strong normative component as it reflects a subjective choice about how the current and future state of the world can best be described or how it *should be*.
- ***Baseline assumptions*** are strongly related to the socio-economic scenarios above (see section 17.4.3.2). Typically, they reflect expectations about future development in the absence of (additional) climate policy, representing a reference against which to compare mitigation costs in policy scenarios. Average and total mitigation costs (e.g. GDP losses or additional energy system costs) are calculated according to the difference between the policy and baseline scenarios. Baseline scenarios reflect the level of challenges for mitigation, with higher baseline emissions increasing mitigation costs substantially or even leading to infeasibility.
- Common ***policy assumptions*** for scenarios in global models are that a *global uniform* carbon price is imposed indicating that global climate action and that mitigation action can be implemented more or less immediately (see section 17.4.3.3). To reflect the inherent political-economy uncertainty of future scenarios, studies have assessed the impact of several alternative policy assumptions:
  - **Fragmented action** typically increases mitigation costs in global models. For EU-specific models, results depend on assumptions about impacts on global output (affected demand for EU exports) and competitiveness. Global action is typically found to reduce

mitigation costs for the EU or even lead to positive GDP impacts if models allow for pre-existing inefficiencies.

- The **exclusion of certain sector from carbon pricing** also typically increases required carbon price levels in the remaining sectors. Some studies for example assume that in sectors such as land-use, for which emission pricing is harder to put into practice, emissions are not subject to the same carbon price level or even excluded from carbon pricing.
- A **delay in climate action** increases mitigation costs substantially in both global and regional (EU) models, partly leading to infeasibility or prohibitively high carbon prices.
- Policy scenario assumptions may also define **mitigation policies beyond carbon pricing** (partly as part of SSP storylines), such as energy efficiency measures or innovation policies. Depending on the model structure, these may be modelled explicitly or proxied, e.g. by parameter choice. As these policies contribute to mitigation, they decrease the level of carbon price needed to achieve a given mitigation effort. Energy efficiency improvements have been found to play an important role, especially in EU studies.

► Similar to socio-economic scenarios, studies frequently compare results for different temperature limit scenarios or carbon budget scenarios (see section 17.4.3.4). Scenarios defining the ***emissions or temperature limit to be used in a 'What-if' analysis*** define the different constraints to be imposed for the cost-effectiveness analysis. However, the choice and definition of these emission or temperature limits have strong normative dimensions, which are highlighted below under 'normative choices'. For the interpretation of mitigation costs for different ambition levels, it should be noted that there is the **risk of selection bias**, caused by a reduced sample population due to the varying ability of models to find feasible solutions to very high mitigation scenarios. This is an area of on-going scientific research within the mitigation modelling community.

The implementation of assumptions that vary between pathways is also related to various **normative (policy prescriptive) choices.** The most relevant are:

► *The* ***emissions or temperature limit in Cost-Effectiveness Analysis*** (see section 17.4.3.4) is a clear normative choice for policy making, with the Paris Agreement providing a clear benchmark since 2015. However, there are many additional related choices with a strong normative character which leave room for interpretation about what is considered in line with the Paris Agreement. Together with the net-zero greenhouse gas mitigation goal expressed in Article 4, the temperature goal of "well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels" (Article 2) allows for two interpretations: holding warming below 1.5°C, or allowing for a temporary overshoot above the 1.5°C limit, while holding warming to 'well below 2°C', implying a better than likely (66%) chance which was previously associated with the pre-

Paris 'below 2°C' goal. The IPCC Special Report on Global Warming of 1.5°C has constrained plausible overshoot pathways to no or low overshoot pathways that are as likely as not to limit warming to 1.5°C. Thus, an important normative choice is whether a scenario defines the temperature limit as an 'end-of century' limit allowing for ***temporary overshoot*** or whether it is defined as a strict limit not allowing overshoot. Depending on the allowed overshoot, two scenarios labeled '1.5°C' may refer to very different peak mean temperature changes and associated climate damages. Another important choice is the ***probability*** with which the mean temperature changes are projected to be below the defined limit.[325] A higher probability is associated here with a more ambitious limit and lower expected damages. The probability reflects remaining large scientific uncertainties related to the climate system and translating emission levels to temperature changes. More ambitious temperature limits are generally associated with higher mitigation costs, though strong variations across socioeconomic scenarios are still observed, including infeasible scenarios. Scenarios allowing for high overshoot in combination with high discount rates typically shift the mitigation burden into the future and yield lower carbon prices in earlier years at the expense of steeply increasing carbon prices towards the end of the century (especially in models conducting intertemporal optimisation).

- Pathways may also differ with regard to assumptions on the regional distribution of mitigation and ***burden sharing*** (see section 17.4.5). Global models frequently assume that mitigation is carried out where it is cheapest globally, disregarding political realities and aspects such as historical responsibility or financial transfers. In reality, the distribution of mitigation activity between regions is unlikely to follow this chosen idealised setting, therefore likely leading to higher mitigation costs. Moreover, many global models apply so-called 'Negishi-weights' which 'freeze' the current global unequal income patterns to avoid model-driven large financial transfers and income redistribution. National or regional models need to make assumptions on what is considered to be the 'fair share' for the specific region or country. In global models, various burden sharing schemes may be applied to distribute mitigation efforts between regions or countries with limited agreement on which scheme can be considered 'fair'. Alternatively, models can assume fragmented action (i.e. only certain regions implementing mitigation measures), typically increasing mitigation costs.

- An important normative choice is the ***discounting scheme and related parameters*** (see section 17.4.4). While in cost-effectiveness models the discount rate does not affect the (pre-defined) mitigation target choice per se, it has a direct impact on the transformation pathway over time, the technology mix and the amount of overshoot and thus the associated damages. Reflecting the valuation of future costs, discounting has strong implications for intergenerational justice, as higher discount rates shift mitigation efforts and the associated costs into the future. This is especially relevant, for example, for large-scale deployment of (costly) potentially risky technologies such as negative emission technologies. For higher discount rates, future generations are thus burdened with i) a higher mitigation burden, ii)

[325] Probabilities typically found in the literature are 50% and 66% or 67% (two thirds probability rounded).

the risks that currently immature technologies do not keep up with current expectations (on effectivity and technology cost development) and iii) potential higher risks from climate damages due to increased overshoot. In the current literature, commonly found discount rates in mitigation cost models are around 5% and underlying discount rate levels often lack transparency. In contrast to the literature on the Social Costs of Carbon, the role of the discount rate choice in mitigation cost models is rarely discussed in the literature and sensitivity analyses with regard to different discount rates are scarce. The few existing sensitivity analyses show that higher discount rates strongly affect mitigation costs and their intertemporal distribution. We therefore recommend encouraging more sensitivity analyses applying different discount rate values, especially lower discount rates.

- Modelers typically have large discretion over how they implement techno-economic assumptions in the form of ***constraints on technology options*** (see section 17.4.7), e.g. for implementing socio-economic storylines.
    - These constraints can be related to **restricting the use of certain technologies**, e.g. nuclear or CCS to reflect policy decisions for example due to a lack of public acceptance or sustainability limits for BECCS or biomass, up to excluding certain technologies. It may also include the choice of which (low carbon) technologies are explicitly represented (e.g. hydrogen). In the last years, there have been many developments with new technologies such as hydrogen or Direct Air Capture, that have remained underrepresented in many global or even regional mitigation cost model studies at the time the literature was reviewed for this study.[326] Taking these new developments into account could decrease mitigation costs and carbon price levels – especially over the longer run. The exclusion of technology options, e.g. nuclear or biomass, typically increases mitigation costs (assuming they would have been cost competitive). Restricting BECCS has been found to strongly impact costs and cost dynamics. The exclusion or restriction of negative emission technologies (NETs) have implications for the intertemporal distribution of efforts as lower near-term efforts cannot be compensated by negative emissions in the second half of the century, increasing near-term mitigation costs. Other NETs beyond BECCS (e.g. Direct Air Capture, DAC) have been identified as potentially providing a viable and affordable alternative in the future (see section 17.4.8.2).
    - Constraints may also **limit the speed of phasing out conventional (carbon intensive) technologies**, for example assuming system inertia, or **scaling up new (low carbon) technologies**, or impose restrictions on the energy mix to proxy **system stability** concerns. Also, this may partly be a result of assumptions about technological change and technology cost developments. Models including higher technological details (e.g. due to focusing on certain regions or on the energy sector only) can represent these types of constraints with higher detail. While the starting point of these assumptions may be of a descriptive nature, the implications of the results can be policy-prescriptive.

[326] Given that this study strongly draws on meta-analyses and model intercomparisons to assess the relevant factors explaining differences in mitigation costs between models and pathways, and these studies typically build on previously published literature, there is a certain time lag until new developments in the scientific community are represented and analysed in these kind of studies.

Global models have typically strongly overestimated the future technology costs of renewable energy technologies and underestimated the growth rate of low carbon technologies like wind and solar compared to what can be empirically observed. This assumed slow expansion of renewable energy technology options, which has been common in many global models, moreover affects the resulting technology mix, suggesting that a slower replacement of fossil fuel technologies would be needed and resulting in a higher need for CCS and negative emission technologies to compensate for those emissions. More favorable assumptions for renewable energy diffusion typically decrease mitigation costs, especially in combination with endogenous technological change and learning by doing. Moreover, underlying historical data may be outdated.

In how far scenario and normative assumptions can be harmonized across models also partly depends on the **model-specific** characteristics. Model-specific factors can further be differentiated into

- ***structural elements*** characterising the inherent model set up choices or
- elements of a model that may be included or excluded in different model versions but still represent some form of structural modules characterising the model (in the following called ***exclusion/inclusion choices***).

Important **structural elements** that have an impact on mitigation costs are all factors discussed under general model structure as well as some additional fundamental model characteristics such as:

- With regard to the **economic system representation and equilibrium type** of a model (see section 17.4.6)**,** three different groups of models are most frequently used in the literature: i) bottom-up (partial equilibrium) energy system models making exogenous assumptions on economic activity outside of this sector and typically minimising energy system costs, ii) whole-economy Optimal Growth models featuring a simplified representation of the economic system and iii) Computable General Equilibrium (CGE) models featuring a detailed representation of sector interlinkages, with the latter two typically maximising welfare (in the form of consumption) and taking a top-down perspective.[327] These model types have in common that they typically assume some form of partial or general (economy-wide) equilibrium and optimisation process. An alternative less frequent type are 'non-equilibrium' models questioning this assumption. Regarding sectoral representation, models also vary in the way they represent end-use sectors (for example, the industry, transport or buildings sector), as well as in their representation of the land-use sector or aspects related to trade (see section 17.4.11).
  - *Technical limitations and scientific uncertainty*: The increased complexity on one end typically comes at the expense of reduced complexity in other regards. For example, energy-system models with high technological detail lack interactions with other sectors. Optimal Growth-type models largely abstract from representing complexities of the

[327] Models may also conduct a combination of minimising energy system costs and maximising welfare through coupling of (sub-)models.

economic system to focus on development over time. Moreover, economic systems and dynamics in feedback effects are still poorly understood. CGE-type models, depicting complex interactions between sectors and between different agents, are confronted with the challenges of limited knowledge of how sectors and agents interact with each other and uncertainty about how these interactions will change due to necessary (profound) structural changes. CGE models often need to rely on static snapshots of current structures which will not well represent required future structural changes.

- *Normative aspects*: The model type choice sets different priorities. Energy system models often highlight 'engineering' challenges in the energy system implying that impacts on other sectors are less relevant (though there are exceptions). Optimal Growth models highlight the long-term development perspective implying that – while whole economy impacts are relevant – impact channels for different actors or sector interlinkages can be disregarded. CGE models highlight the importance of these impact channels and interlinkages. More importantly, however, both PE and GE models assume that the economy is in a certain equilibrium in the absence of climate policy. This assumption– *per definition* – leads to climate policy always imposing negative macro-economic impacts and thus reflects a certain world view that can be challenged.
- *Impact on mitigation costs:* Mitigation costs tend to be higher in General Equilibrium models compared to Partial Equilibrium models as the latter focus on engineering type-costs disregarding feedback effects and implementation barriers for the wider economy. PE and GE models both assume some form of equilibrium and optimisation process. However, it should be noted that starting from the assumption that the economy is in equilibrium before introducing climate policy by definition imposes macro-economic costs resulting from climate policy (deviation from equilibrium). This reflects a certain world view, which is challenged by models that relax assumptions of perfect market equilibrium conditions allowing for pre-existing inefficiencies (e.g., so far less frequently used 'non-equilibrium models') in which climate policy can even lead to economic gains (e.g. positive GDP impacts of mitigation). CGE models tend to exhibit higher mitigation costs as they account for economy wide interactions and distortions (such as tax interaction effects). Higher costs in CGE models compared to Optimal Growth models are also related to differences in the foresight mechanism typically applied in those model types (see section 17.4.6.4). Differences in sectoral representation can also have implications for mitigation costs. If barriers to the electrification of transport or in other end-use sectors are represented, models find that substantially higher carbon prices are needed to compensate for these mitigation challenges (see section 17.4.11and 17.6). Likewise, assuming limited possibilities to control emissions from land-use imply the need for higher carbon prices in other sectors to remain within the same temperature limit (see section 17.4.11.). If the various sectors are not modelled explicitly, challenges (or opportunities) towards decarbonising these sectors may not be adequately reflected by these models.

- Linked to the choice of equilibrium type and economic system representation is the choice of the applied **foresight and solution mechanism** (see section 17.4.6.4)**.** The two main types that can be differentiated are applying i) a *recursive dynamic approach* solving based on information given in each time step ('myopic expectations'), typically applied by CGE models or ii) a forward-looking *intertemporal optimisation* approach optimising over the whole time horizon ('perfect foresight'), typically applied by Optimal Growth models.
  - *Technical limitations and scientific uncertainty:* Models with higher complexity in representing, for example, economic agents or sector interlinkages (CGE models) or technology details (energy system models) typically reduce computational complexity by applying a recursive dynamic approach for each time step. Yet, they still need to make assumptions about future costs which are subject to large scientific uncertainties. To conduct intertemporal optimisation, perfect foresight models need to assume that future cost developments, technology availability and future economic conditions are fully known at any point in time decades ahead despite uncertainties in projections. To enable this intertemporal optimisation Optimal Growth models typically reduce complexity in the form of simplified economic system representation. Regional models typically have a shorter time horizon (e.g. until 2050) as the accuracy of any projections decreases strongly over time, while many global models use 2100 as an end-point.
  - *Normative components*: As the recursive dynamic approach takes investment decisions based on information available in the respective period, the approach may be considered to better reflect reality compared to assuming perfect foresight. However, myopic behavior can trigger different 'short-sighted' investment strategies, e.g., leading to stranded assets. Perfect foresight models aim to provide insights on what would be intertemporally optimal from a foreword-looking perspective.
  - *Impact on mitigation costs:* Perfect foresight Optimal Growth models tend to yield lower mitigation costs compared to CGE models, at least in the short run. However, the intertemporal dynamics differ for these models, with exponential growth in carbon prices yielding high carbon prices towards the end of the century. Perfect foresight models can allocate emission reductions more efficiently over time by optimising over the full time horizon, leading to lower mitigation costs compared to whole economy models applying step-wise optimisation of a recursive-dynamic approach. However, while recursive-dynamic approaches yield higher carbon prices in the short run, these increase more modestly in the long run compared to perfect foresight models performing intertemporal optimisation typically exhibiting exponential price developments.
- The representation of **technological change** (TC) (mainly referring to the energy sector) is another important structural element (see section 17.4.7.2). Broadly, models can be grouped into those that model technological progress exogenously and those that feature some representation of endogenous technological change, allowing for a portion of technological change to be influenced by deployment rates, market and policy incentives or investments in

research and development (R&D). The representation may however differ for different technologies in the same model.

- *Technical limitations and scientific uncertainty*: Assumptions on technology cost projections decades into the future are inherently uncertain. Endogenising technological change increases model complexity.
- *Normative aspects*: Models with endogenous TC assume that technological progress and innovation is at least partly driven by 'learning by doing', implying that investing in deploying more new technologies will foster learning and bring down costs or even bring new technologies to a level of maturity needed for 'off-the-shelf' deployment. Studies suggest that low carbon technologies could become the least-cost options due to induced technological change (see section 17.4.7.2) creating a positive 'path dependency' effect for decarbonisation. This has normative implications for policy making.
- *Impact on mitigation costs:* Intertemporal optimisation models which assume perfect foresight supplemented with endogenous technological learning tend to find lower aggregated mitigation costs compared to the models with no endogenous representation of technological change. Endogenous TC also tends to incentivise earlier investments in low-carbon technologies, bringing down costs for future periods (increasing mitigation costs in the shorter term).

► Not all models have full **coverage of GHGs**, some focus on CO_2 only (see section 17.4.6.3). While CO_2 is dominant for the energy sector, non-CO_2 emissions play an important role in other sectors like agriculture or industrial processes or sewage treatment.

- *Technical limitations and scientific uncertainty:* Converting GHGs into CO_2 equivalents is subject to uncertainty and ongoing scientific debate, with conversion factors having been revised across the IPCC's Assessment Report cycles.
- *Normative components:* Focusing on CO_2 only puts low emphasis on the role of sectors which feature a higher share of non-CO_2 emissions, such as agriculture.
- *Impact on mitigation costs:* A multi-gas approach allows for more mitigation flexibility, reducing costs. However, mitigation of non-CO_2 gases is partly found to be more challenging, for example abating emissions from livestock, fertiliser use, and land-management while for other examples (e.g. nitrous oxide destruction in industrial processes) non-CO_2-abatement can be comparably cheap

Elements we would consider **'exclusion/inclusion choices',** i.e. elements of a model that may be included only in certain model versions, are

► The positive (or negative) **side-effects of mitigation action** may be taken into account when assessing mitigation costs (see section 17.4.9). This includes the choice of which modules (and sectors) are covered explicitly in the model suite, e.g. whether models account for trade-offs with land-use or agriculture or employment impacts or are coupled with air quality models assessing air pollution and related health impacts. This requires the valorisation of such (non-monetary) co-benefits, e.g. health implications by applying approaches such as the 'statistical value of life' for monetarising benefits and costs involving value judgements. Several studies accounting, for example, for health co-benefits find that these could partly or even fully outweigh mitigation costs in certain regions. Other co-benefits are reduced fuel import bills and increased energy security.

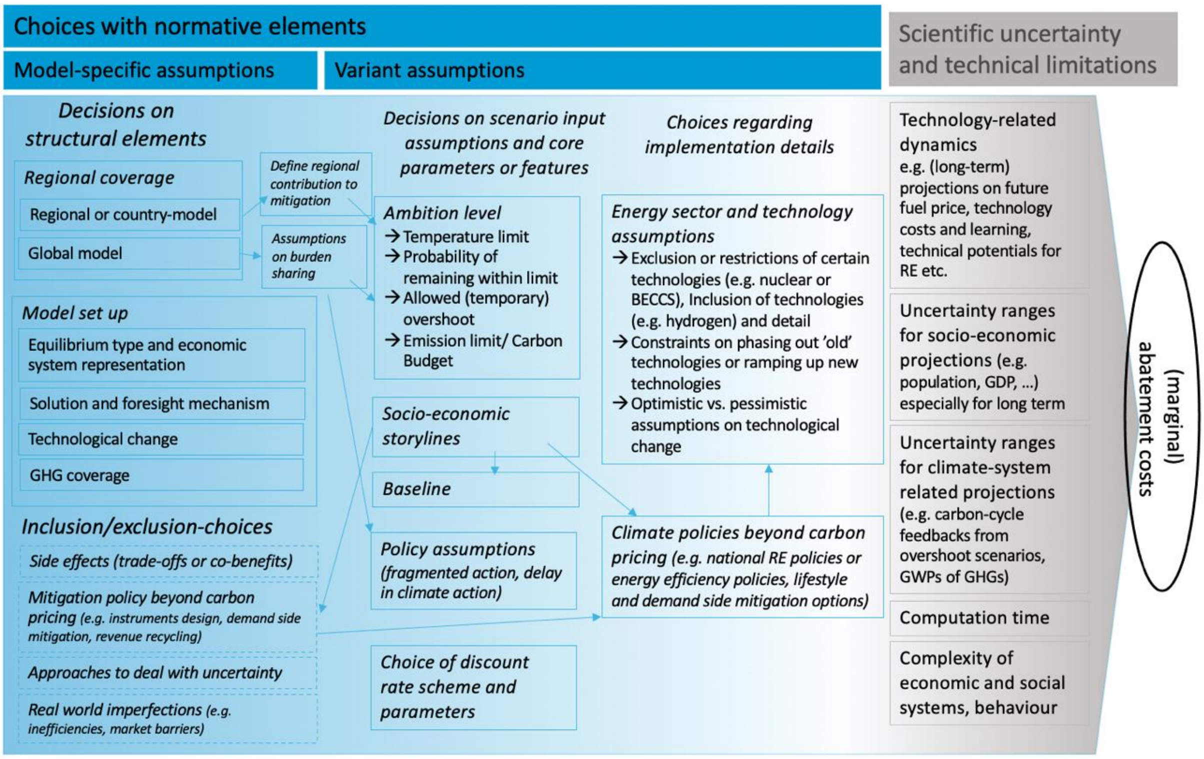
- Models differ in their ability to **represent mitigation policy options** (see section 17.4.8.3). Some models allow explicit modeling of **policy instrument design** for mitigation such as efficiency standards or support measures for specific (low carbon) technologies, which may also be part of the baseline (existing policies), socio-economic storylines or policy scenarios. The analysis of these kinds of policies typically plays an important role in regional or national models, in which a global carbon price may not be the main driver of emission reductions. Making full use of **energy efficiency** measures has been identified as an important factor for a successful decarbonisation strategy in EU level studies. The role of so-called **demand side mitigation options** has recently gained attention in the literature, for instance in so-called Low-Energy-Demand (LED) scenarios. These show that changes in consumption patterns towards more sustainable lifestyles (e.g., reduced electricity use, dietary changes) can substantially reduce mitigation costs and, to some extent, may even allow to reduce the role of negative emission technologies, at least in part. For carbon pricing, the design of the **revenue recycling scheme**, i.e., how revenues from carbon pricing are redistributed, have also been shown to play an important role with regard to mitigation costs.

- The representation of "**real world imperfections**" such as inefficient use of resources and imperfectly functioning markets can form part of the general model (e.g., in non-equilibrium models), but can also be proxied by, for example, cost mark-ups or parameter choice in equilibrium-based models. Yet, scientifically, there is still a lack of understanding of economic and social systems, and behavioral patterns. The frequent assumption of a 'representative agent(s)' acting fully rationally does not reflect reality well. Pre-existing inefficiencies allow for negative cost options, but market barriers can also increase mitigation costs.

- Some models include **methods for dealing with uncertainty** such as stochastic approaches. However, the number of parameters that could be varied is very large. Thus, mitigation cost models rarely use stochastic approaches to deal with uncertainties. More common are sensitivity analyses or model inter-comparisons.

Figure 104 summarises the different influencing factors for mitigation costs.

Figure 104: Overview on (normative) choices and scientific uncertainty



Source: own illustration, Climate Analytics

In a nutshell, models assessing long-term transformation pathways for a given mitigation target are very heterogenous and generalisation is thus challenging. To provide insights on least-cost transformation pathways and resulting implications for the technology mix as well as the associated mitigation costs, these models link several highly complex systems, each of which individually is not yet well-understood. This leads to large scientific uncertainties. Different model types have their strengths in answering specific questions while failing to provide answers to all questions. A complementary analysis combining insights from different types of models is thus recommended.

Furthermore, it is largely at the discretion of the modellers how normative choices and technical uncertainties are implemented in the models. Many of these normative assumptions are partly hidden in the model structure or choice of parameters and are often not transparent or require an intense study of model documentation (which is often lacking or outdated). Efforts have been made by the modelling community to improve model documentation and transparency. However, this requires constant investment in documentation updating and extension. The overall complexity of the models, and the sheer quantity of underlying parameters and input data (which can change for each scenario), is challenging to document in a transparent way.

While there are a variety of open-source energy system models,[328] only few global models allow deeper insights into their model code or data[329] and would allow interested users (presuming the required technical skills and software licenses to run the models are not an additional barrier) to test the sensitivity of the model outcomes with regard to changing underlying scenarios and (normative) choices. The usefulness of model results for policy making therefore strongly depends on whether published studies feature sensitivity analyses that use a set of — intellectually accessible —scenarios and (normative) choices that come close to the policy maker's preferences. A policy maker may also commission models to run specific analyses and provide appropriate documentation.

The scientific objectivity of many mitigation cost models has been called into question for "substituting messy and contextual politics with non-contextual mathematical formulation"[330] while maintaining their "optimism for ongoing technocratic approaches"[331]. Clearly, models have strong limitations as to how well they are able to reflect reality and real-world complexity and even more so represent socio-political aspects. As a result, mitigation cost estimates (or other model outcomes) should not be interpreted as 'accurate' predictions - especially given the underlying long-term horizon. Yet, bearing the limitations in mind - cost-effectiveness-assessments of long-term mitigation pathways can be useful tools for systematically asking "'what-if' questions to envisage future consequences of decisions and developments"[332] to increase the understanding of which radical changes are required and the order of magnitude of the associated policy costs (total costs) and the level of carbon price required. However, insights from other disciplines are required to understand which of the potential pathways are deemed more feasible from a social, political and economic perspective.

[328] Find a list under this link https://wiki.openmod-initiative.org/wiki/Open_Models

[329] GCAM for example is available as open source software (http://www.globalchange.umd.edu/gcam/) sharing code and data on GitHub (https://github.com/JGCRI/gcam-core). Also Remind shares code on Github (https://github.com/remindmodel/remind), while MESSAGEix is also on GitHub (https://github.com/iiasa/message_ix) however, requires a licence to run it.

[330] (K. Anderson in (Anderson & Jewell, 2019) p.348).

[331] (K. Anderson in (Anderson & Jewell, 2019) p.348).

[332] (J. Jewell in (Anderson & Jewell, 2019) p.349)

Part 4: Synthesis and Guidance for political use

Section 19 synthetizes the results of Parts 2 und 3. In Section 20 we propose a four-step process to derive climate costs. We strictly focus on the process and do not recommend specific values or ranges for the involved parameters or results.

19 Comparison of frameworks

19.1 Overview

There are two different frameworks to determine climate costs (see further Section 2.1): *Damage* costs, which correspond to the monetized impacts of greenhouse gas emissions and *mitigation* costs, which correspond to the costs that accrue reducing emissions. Cost-benefit analysis is a third framework that considers both in parallel. This third framework is conceptually problematic and has thus not been the focus of this study (see Box 2 in Section 2.1).

In the previous parts of this study we analysed and derived the most relevant influencing factors of the damage costs and mitigation costs frameworks (see especially the respective findings in Sections 15 and 18). This Section aims at listing and comparing those influencing factors in a comprehensive way.

19.2 Categorization and comparison of influencing factors

Both frameworks have various influencing factors that introduce uncertainty. Correspondingly, the literature's model results have a considerable range in both cases. We identify relevant influencing factors and sort them into four categories. We also show in which form an authority that commissions model runs (in the following called 'contracting authority'; see further Section 20) can possibly reduce the uncertainty range. The four categories are as follows:

- **Structural elements**: Influencing factors of this type are essential elements of any model. They feature scientific uncertainty (see also Section 2.3.3), related to lacking data as well as incomplete understanding of the natural science (geophysical processes of the earth system) and (economic) processes. Those influencing factors are the subject of ongoing scientific research and debate and thus modelers use different approaches (e.g. with respect to functional forms) and calibrations to address them. For that reason, the contracting authority has little means (other than choosing or excluding a certain model completely) to demand or exclude specific approaches, as it is hardly able to intervene in the scientific process.
- **Normative choices** are also essential elements of any model. Yet, they by definition they cannot be based on data but have to be prescribed by the user of the model. The contracting authority ought to prescribe parameters that reflect its social preferences (if such information is available). Those choices have to be made transparent and sensitivity analyses are recommended to reflect different preferences of the users.
- **Exclusion choices**: Influencing factors of this type are elements of a model for which the exclusion (or inclusion) of a certain model element is an explicit choice by the contracting authority. Exclusion (or inclusion) implies a normative choice, also depending on the policy objective. If included, such an element is essentially analogous to an essential element in the sense that it features scientific uncertainty. The contracting authority can thus prescribe inclusion (on-off choice), but it can hardly influence the specific implementation.
- **Scenarios** are essential inputs for any model (see further Section 2.4). They are either a set of projections of possible futures (e.g. related to emissions of greenhouse gases, economic growth, or population growth). As such, this type of uncertainty cannot be reduced by the

contracting authority. In some cases, however, the choice of a specific scenario or set of scenarios is normative and should thus not be left to the discretion of the modelers. Examples are a temperature limit (for mitigation costs) or a low policy ambition scenario to raise awareness of the costs of inaction (for damage costs).

In the following, we sort all relevant influencing factors (as derived in the previous parts) into these four categories. This is only a tentative categorisation: while the sorting is uncontested for some factors (e.g. the choice of the pure rate of time preference is a clear example of a normative choice), for other factors the distinction is more blurred and different aspects of one influencing factor may fall into different categories.[333]

The tables also contain our estimate of the uncertainty caused by the influencing factor. A low influence on the cost-range implies that varying assumptions on that factor have limited impact on climate costs and vice versa. The rating reflects the judgment of the authors, based on the analysis of the main parts and on feedback from external experts. It must be acknowledged, however, that such a rating is not possible in an objective and all-encompassing way. It rather depends on the setting (that is, on the model choice and on the specific assumptions with respect to the other factors) and may be wrong in specific cases. For example, if the discount rate is increased, the relevance of influencing factors that concern the far future (e.g. catastrophic climate change) will decrease.

With these two caveats in mind, the following tables categorise the influencing factors and depict the respective impacts on the cost-range.

[333] Consider as a specific example the parameter of inequality aversion, which we consider a normative choice. However, for some users it may not be obvious what their preferred inequality aversion is. This parameter is conceptually more complex and less commonly discussed than the pure rate of time preference. In addition, impacts are less clear, as it may impact intergenerational, interregional inequality as well as risk aversion. Inequality aversion may thus also be considered an essential element featuring scientific uncertainty.

On a more general level, a non-expert has little choice but to categorize an ongoing discussion in the literature as scientific uncertainty. A more in-depth analysis will reveal, however, that the discussion reflects underlying political or philosophical preferences of the involved scientist, which often has a normative character. An example is the damages function, which we consider a scientific uncertainty. Yet, a closer look may reveal that the contracting authority prefers, say, a sector-specific enumeration instead of an aggregated approach. After a yet closer look it may demand certain sectors to be included or even change the way the damages are modelled based on value judgment.

19.2.1 Scenarios

Table 41 depicts the scenarios.

Table 38: Indicative rating[334] of Influencing factors: Scenarios

Scenarios	Influence on cost range Damage	Mitigation	Reasons for uncertainty range
Emission scenarios	**	–	Damage: Emission scenarios provide ranges from modest to strong future climate change (e.g. RCP-scenarios) Mitigation: In the mitigation cost setting, future emissions are a normative choice (see "emission or temperature limit" in Table 39).
Socio-economic scenarios	**	***	Damage: Economic and population growth rate affect damage estimates and discounting. Mitigation: Assumptions on economic development, population growth, energy demand, lifestyle, other techno-economic parameters, and price of fossil fuels.
Baseline scenario	–	**	Damage: Not relevant Mitigation: Socio-economic scenario without additional climate policy for comparing impacts of policy scenarios. (Average and total) mitigation costs are calculated based on the difference between policy and baseline scenario. Also known as reference scenario.
Policy assumptions on delay and fragmented action	–	***	Damage: Not relevant Mitigation: Fragmented action increases mitigation costs compared to global action. Delaying ambitious climate action has been found to increase cost substantially up to prohibitively high carbon prices or infeasibility.

Rating: low / medium / high influence: */**/***

Source: own illustration, Infras/Climate Analytics

19.2.2 Normative choices

Table 39 depicts the normative choices.

Table 39: Explanation and indicative rating[335] of influencing factors: Normative choices

Normative choices	Influence on cost range Damage	Mitigation	Reasons for uncertainty range
Temperature limit	–	***	Damage: Not relevant. Damage models do not use limits but emission scenarios (listed in the category "scenarios") Mitigation: A limit has to be prescribed to calculate mitigation costs. Either a limit on emissions ('carbon budget'), on temperature, or on atmospheric concentrations.

[334] The qualitative ratings in the table are based on expert judgment building on insights from the previous report chapters and feedback in a workshop with external experts. Due to differences in underlying concepts, the ratings for mitigation and damage cost sides are not directly comparable but are relative to other factors for the respective framework.

[335] The qualitative ratings in the table are based on expert judgment building on insights from the previous report chapters and feedback in a workshop with external experts. Due to differences in underlying concepts, the ratings for the mitigation and damage cost sides are not directly comparable but are relative to other factors for the respective framework.

Normative choices	Influence on cost range Damage	Mitigation	Reasons for uncertainty range
Risk management choices	**	**	Damage: A high risk aversion increases damage estimates in a non-deterministic setting. Mitigation: For a given temperature limit, demanding a certain probability to reach that limit results in different associated carbon budgets (esp. relevant for ambitious limits). Allowing temporary overshoot of the carbon budget increases peak temperature changes which may trigger tipping points.
Discounting scheme and related parameters	***	***	Damage: Defines the current value of future damages. Appropriate scheme and respective parameter must be specified (discount rate for fixed or declining discounting scheme; pure rate of time preference, growth rate and inequality aversion for Ramsey discounting scheme. Mitigation: High discount rate typically shifts mitigation action into the future and affects the technology mix (esp. use of negative emission technologies).[336] Does in principle not influence the aggregated mitigation effort in the long run, which is prescribed by the emission or temperature limit, but can affect the level of overshoot.[337]
Time horizon	**	**	Both: Choice of discount rate plays larger role for longer time horizons. Damages: Only relevant if discount rate is rather low and there is low policy ambition. Then, choosing a longer time horizon substantially increase SCC. Mitigation: Uncertainty increases with time scales. Defining a carbon budget until 2100 (without fixing interim targets) allows distributing mitigation efforts until the end of the century. Combined with high technological learning and negative emission technologies or high discount rates, this incentivizes shifting mitigation into the far future, reducing short-term costs at the expense of future costs. National models typically chose shorter time horizons (2050 or 2030).
Equity weighting/ Burden sharing	***	**	Damage: Equity weighting concerns valuation of damages in poorer countries as compared to richer countries. It is influenced by inequality aversion and with may also affect the discounting scheme. Mitigation: Burden sharing scheme influences the regional distribution and the overall costs. Least-cost global action implies large mitigation share for poor countries (at least initially), which could in principle be compensated by transfers. Fragmented action increases costs.

336 Note the difference between damage costs and mitigation costs in this respect. Suppose we increase the discount rate. For damage costs this implies a lower SCC irrespective of the time of the emission. For mitigation costs (given a certain limit), however, this implies shifting the mitigation burden into the future. Mitigation costs thus decrease in the near future but increase in the far future.

337 For example, a 1.5°C temperature limit by the end of the century is associated with a certain carbon budget. Allowing for temporary overshoot of this carbon budget, a large-scale deployment of negative emission technologies in the second half of the century can compensate for high emissions in the first half. This would allow to technically remain within the overall carbon budget labeled ‘1.5°C’ but increases peak temperature changes compared to no-overshoot 1.5-pathways. High discount rates push mitigation to the future and thus incentivize high overshoot.

Normative choices	Influence on cost range Damage	Mitigation	Reasons for uncertainty range
Constraints on certain technology options	–	***	Damage: Not relevant. Regarding adaptation technology, constraints may be related to geoengineering, which however has not been considered in this study. Mitigation: If certain technological options are assumed socially unacceptable (e.g. nuclear or BECCS) or are neglected in the model (e.g. other negative emission technology options), this substantially increases cost and affects its intertemporal distribution. Also, system inertia assumptions cap the growth rate of new technologies or slow phasing out conventional ones.
Cost concepts	*	*	Damage and Mitigation: This refers e.g. to the choice whether to use average or marginal costs (see Box 1).

Rating: low / medium / high influence: */**/***
Source: own illustration, Infras/Climate Analytics

19.2.3 Structural elements

Table 40 depicts the structural elements.

Table 40: Explanation and indicative rating[338] of Influencing factors: Structural elements

Structural elements	Influence on cost range Damage	Mitigation	Reasons for uncertainty range
Climate system	**	* / —	Damage: A given emission trajectory causes complex geophysical impacts and there are various feedback mechanisms in the earth system. A common — albeit conceptually contested — metric is the climate sensitivity, which is notoriously difficult to determine. Uncertainty increases in the long run. Mitigation: If input is temperature limit, a probability level has to be assigned before it can be operationalised using an emission budget (or pathway). Not relevant if carbon budget is directly used as input.
Damage function	***	—	Damage: Translation from geophysical impacts to monetised damages must consider multiple sectors over time. Reliable data on a global scale are scarce and no model provides a fully integrated estimate for all sectors and potential processes. Mitigation: Not relevant by definition: Cost-Effectiveness-models do not account for climate damages.
Adaptation	**	—	Damage: Decreases damages (locally and in specific sectors). May entail specific costs or occur autonomously. Is either accounted for explicitly or implicitly as "net" damage function (or even not at all). Mitigation: Not relevant by definition: Cost-Effectiveness-models do not account for climate damages and by implication also not for adaptation.
Technological change	**	**	Damage: Affects adaptation costs and thus net damages.

[338] The qualitative ratings in the table are based on expert judgment building on insights from the previous report chapters and feedback in a workshop with external experts. Due to differences in underlying concepts, the ratings for mitigation and damage cost frameworks are not directly comparable but are relative to other factors for the respective framework.

Structural elements	Influence on cost range Damage	Mitigation	Reasons for uncertainty range
			Mitigation: Optimistic assumptions on learning curves decrease future mitigation costs (both for exogenous or endogenous learning curves). Perfect foresight models combined with endogenous learning find lower aggregated mitigation costs compared to myopic models, as in the former, 'learning-by-doing' incentivises earlier investments into low-carbon. This decreases future costs but may increase short term costs.
Model design	**	**	Both: Choice of various modelling aspects induces structural uncertainty. Examples are functional forms, objective function (e.g. welfare or energy system costs), model type (e.g. optimal growth, computable general equilibrium (CGE), energy system model), foresight (perfect foresight vs. myopic expectations), sectoral detail and sectoral interactions and coverage of GHGs. Especially relevant for mitigation costs, as a larger diversity of model structures exists. Overlaps with other influencing factors (e.g. "Damage function" or "Technological change").

Rating: not relevant / low / medium / high influence: —/*/**/***

Source: own illustration, Infras/Climate Analytics

19.2.4 Exclusion choices

Table 41 depicts the exclusion choices.

Table 41: Explanation and indicative rating[339] of influencing factors: Exclusion choices

Exclusion choices	Influence on cost range Damage	Mitigation	Reasons for uncertainty range
Approach to deal with uncertainties	***	**	Both: Overarching aspect regarding the choice to use a deterministic setting or accounting for uncertainties from other influencing factors. Possible options are Monte Carlo simulation for parametric uncertainty, ad-hoc adjustments or results-wording[340] for inclusion and deep uncertainty, and model intercomparisons for structural uncertainty. Mitigation models rarely use Monte Carlo simulations, whereas this has become best practice for damages models. Related to risk management choices and final communication of results.
Catastrophic climate change	***	—	Damage: Low probability, high impact events which by definition have high uncertainty regarding probability, timing and impact. They are inherently difficult to monetize. Mitigation: Not relevant by definition: Mitigation models do not account for climate damages
Non-market climate impacts	**	—	Damage: Difficult to monetize as they are non-market. The choice of which non-market sectors ought to be included and

[339] The qualitative ratings in the table are based on expert judgment building on insights from the previous report chapters and feedback in a workshop with external experts. Due to differences in underlying concepts, the ratings for mitigation and damage cost sides are not directly comparable but are relative to other factors for the respective framework.

[340] If certain influencing factors cannot be monetized but are likely to increase costs (e.g. non-market impacts), the results can be labelled as lower bound (see further Section 20.5).

Exclusion choices	Influence on cost range Damage	Mitigation	Reasons for uncertainty range
			which method ought to be used is a value judgment. Different methods yield different results. Mitigation: Not relevant by definition: Mitigation models do not account for climate damages
Side effects of mitigation	–	*	Damage: Not relevant by definition: Models do neither account for costs nor benefits of mitigation. Mitigation: Co-benefits of mitigation (e.g. reduced air pollution) and trade-offs (e.g. competition for land) are assessed in selected models. Co-benefits are found to (at least partly) outweigh mitigation costs, but are typically reported separately.
Representation of mitigation policy options	–	**	Damage: Not directly relevant (indirect effect as policies affect emission) Mitigation: Models differ in their ability to represent policy instruments and design details beyond carbon pricing (e.g. efficiency standards, bans or subsidies). Those can be part of baseline (existing policies), socio-economic storylines or policy scenarios and are especially relevant for regional or national models. Energy efficiency (policies) and demand side mitigation reduce required carbon prices substantially, such that the carbon price does not reflect full marginal abatement costs. For carbon pricing, the design of the revenue recycling scheme also affects mitigation costs, seen from a macroeconomic perspective.
Bounded rationality	–	*	Damages: Not relevant Mitigation: E.g. inefficient use of resources and imperfectly functioning markets. The frequent assumption of 'representative agent(s)' acting fully rational is not reflecting reality. Pre-existing inefficiencies allow for negative cost options, but market barriers and inefficient policy design can also increase mitigation costs.

Rating: low / medium / high influence: */**/***

Source: own illustration, Infras/Climate Analytics

19.3 Uncertainty ranges

Damage costs as well as mitigation costs feature a high uncertainty— which is reflected by the large range of the literature's results. For both frameworks the model design, approaches to deal with uncertainty, several normative choices (especially on discounting), and socioeconomic scenario assumptions introduce a significant uncertainty. For damage costs, additional uncertainty results from the climate system, the damages function (including adaptation), equity weighting, catastrophic climate change and non-market impacts. For mitigation cost, additional uncertainty stems from technological change, constraints on certain technology options, the representation of mitigation policy options or temperature limits.

Based on this comparison, we argue that for damage costs, the uncertainty range is larger than for mitigation costs. On a more general level, this has essentially three reasons.

- For a given potential emission, the costs to avoid that emission roughly accrue at the time the mitigation takes place. If emitted however, damages occur from the emission time into the far future.[341]
- Future warming levels are not yet observed, whereas mitigation cost estimates can be based on data and past learning curves, at least for current or near-future mitigation costs. In the far future however, the uncertainty associated with mitigation costs increases drastically.[342]
- Damages have market but also non-market impacts, and the latter are by definition difficult to account for in a quantitative setting. Mitigation costs on the other hand are mostly[343] related to markets and thus easier to quantify.

We expect the uncertainty ranges to remain at the current level for the foreseeable future. An increasing amount of data with respect to technology costs may improve mitigation models to a certain extent. Yet, such estimates are notoriously error-prone. Advancements related to the damage function will remain sluggish as well. Even though there is a growing literature on actual climate damages, we expect the empirical basis to remain scarce and focused on certain sectors. In addition, extrapolations to higher temperature can hardly be based on data and are thus deceptive.

Finally, judged by the number of models and publications, current research regarding mitigation costs seems to be more active. The IPCC, for example, relies heavily on mitigation cost models (e.g. in the Special Report on 1.5°C) but rarely on damage cost models.[344]

19.4 Relevance of climate cost models for climate policy

Mitigation and damage cost models are complex, incorporating assumptions on numerous influencing factors and results are thus prone to uncertainty (see Section 19.3). Therefore, a correct interpretation of the results requires a sound understanding of the models' assumptions and influencing factors (see Section 19.2).[345] Results should never be taken at "face value" or as accurate predictions of future outcomes. While this is true in general for all types of models, this is especially relevant in the context of climate cost modelling. The long-term horizon of climate change, the inertia of the involved systems as well as the complex interplay of socio-economic, behavioural and physical aspects related to climate change makes the uncertainty severe and multi-dimensional.

Many scholars thus reason that the main contribution of mitigation and damage cost models is not to provide exact numbers but insights: they are a coherent and consistent way to scrutinize complex issues asking 'what if questions' and to make assumptions and approaches transparent.

[341] This comparison may be false if a high discount rate is used. In this case, future damages have little influence and consequently the range for damage costs may be smaller than for mitigation costs, simply due to a low valuation of future costs.

[342] For example, the economy is supposed to be carbon neutral until 2050, but available technological options and their respective costs are unclear.

[343] E.g. bioenergy may lead to loss of biodiversity as well as food security concerns which are also non-market costs. Sufficiency or changes in lifestyles are also difficult to monetize.

[344] SCC have been briefly treated in IPCC's Assessment Report 5, Working Group II contributions, chapter 10 (Arent et al., 2014 cowritten by R. Tol), but will not be part of Assessment Report 6.

[345] See e.g. the related warning on the FUND model's webpage: "It is the developer's firm belief that most researchers should be locked away in an ivory tower. Models are often quite useless in unexperienced hands, and sometimes misleading. No one is smart enough to master in a short period what took someone else years to develop. Not-understood models are irrelevant, half-understood models treacherous, and mis-understood models dangerous." http://www.fund-model.org/ (09.12.2019).

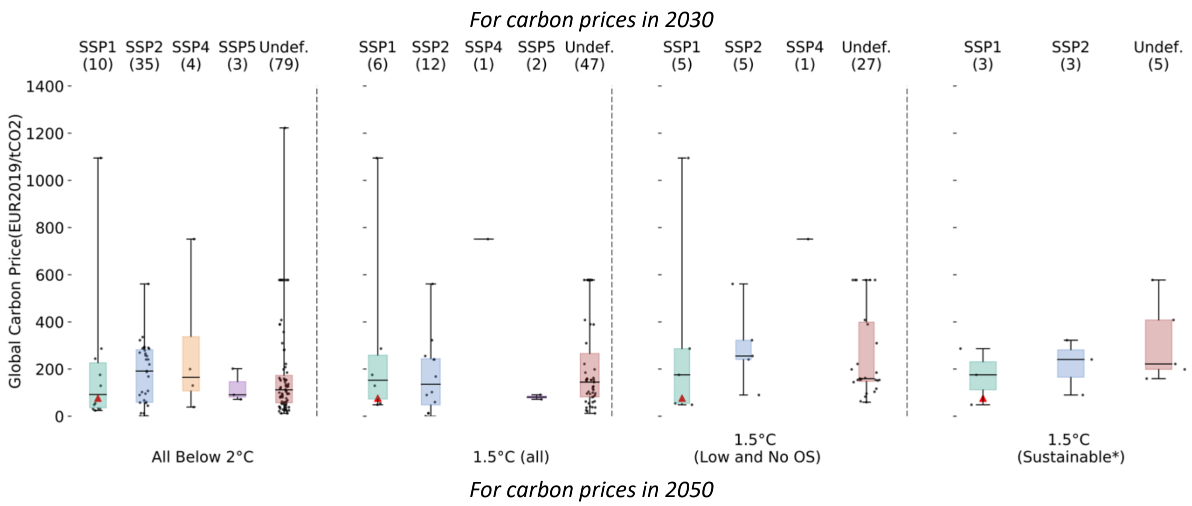
Yet, a price tag on GHG emissions is a crucial part of any climate policy. In the current public debates, the costs and economic impacts of policy choices are a central element to appreciate the relevance of a political issue. Even if uncertainty is high, having an order of magnitude of its costs is key for political decision taking. Not providing such a price just because there is no scientific agreement on the appropriate value is not an option for a policymaker. It is thus reasonable to base the price on model results, as models are an important quantification tool and, importantly, allow for a structured discussion on key influencing factors. As outlined in Section 20, it is in any case important to properly account for the uncertainty.

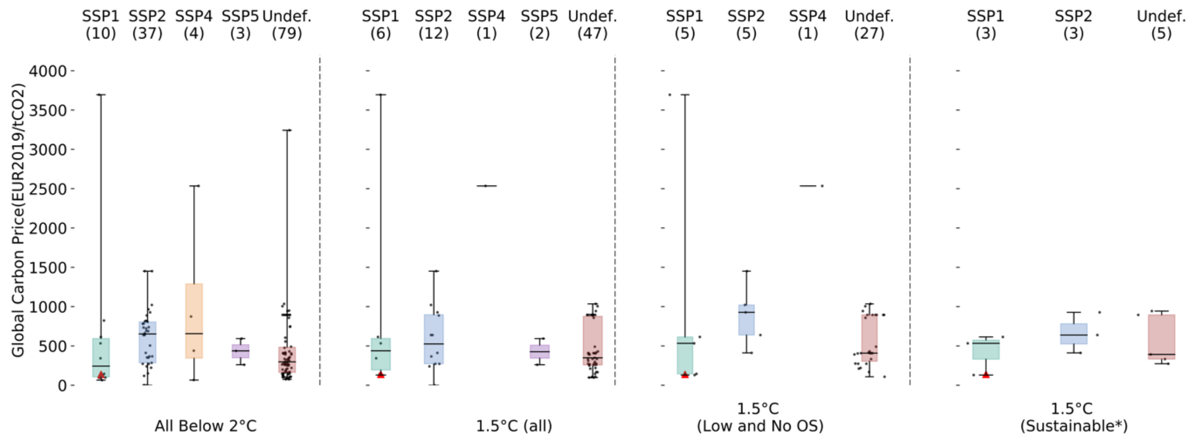
Seen from a wider perspective, a price tag is but one of many elements that a comprehensive climate policy requires. In this wider context mitigation models play a further role: Their primary goal is often to identify and analyse economically or technically optimal system transformation pathways, while the resulting mitigation costs are secondary information. This is especially true for national mitigation models, which identify political fields of action, describe additional investment needs and allow to design a consistent and cost-efficient emission reduction strategy.

19.5 Narrowing down the cost ranges

Fixing normative choices can narrow down the range of climate costs estimates. With the political commitment to the Paris Agreement, the therein defined temperature limit establishes a benchmark for climate policy and resulting normative choices. This is illustrated in Figure 105, where we sequential filter results with respect to such choices, using the scenario database from the IPCC's Special Report on 1.5°C.

Figure 105: Reducing mitigation cost ranges by filtering based on normative choices





Narrowing down the ranges for carbon price estimates (2030 and 2050) for mitigation cost models based on existing scenario databases and normative filtering criteria from left to right. The left column shows the ranges for all scenarios classified by the SR1.5 database as being in line with temperature limits of at least 2°C or more ambitious. The second column excludes scenarios with higher temperature limits than 1.5°C. Out of these, the third column excludes pathways that allow for a high temporary overshoot (OS). Out of the remaining pathways, the last column only shows these that also fulfil certain sustainability criteria (*) limiting the annual maximal potential of applying Carbon Dioxide Removal (CDR) options as defined in the IPCC SR1.5[346]. Carbon prices in USD2010 have been converted to EUR 2019 using the same conversion factors and sources for these as in Figure 54 (UNCTADSTAT 2010) and (Statistisches Bundesamt (Destatis), 2020)). SSP=Shared Socio-economic pathways; "Undef " ('undefined') groups those scenarios that do not provide clear information on the underlying SPP assumptions in the SR1.5 database meta data. The numbers in brackets indicated the number of scenarios on which the respective boxplot is based on. The red marker marks the Low Energy Demand (LED) Scenario.

Source: own illustration, Climate Analytics based on SR1.5 database (Huppmann et al., 2019).

Note that the literature will not allow to account for all normative choices, as certain influencing factors are typically not made sufficiently transparent or the literature does not cover a broad range of assumptions that allow filtering. In current databases for mitigation pathways it is for example not possible to filter for different discount rates, which are typically not reported (or hidden in model documentation) and there are no sensitivity analyses.[347]

Analysis of the filtered ranges for mitigation costs requires a call for caution: Scenario databases typically do not contain information whether the filtering criteria has resulted in infeasibility for some models – implying that the cost increases to infinity and the model can no longer find a solution under the given conditions – which do thus not report cost estimates for the filtered selection of criteria. This can lead to a selection bias in cost ranges, underestimating costs especially for more ambitious scenarios, as only models with more optimistic assumptions (in terms of substituting technologies, available mitigation options, and baseline assumptions) report results (Tavoni & Tol, 2010). The implications of potential infeasibility issues have thus to be kept in mind. On the other hand, the absence of pathways for a specific filter should also not be interpreted as indicating infeasibility, it can also be that models simply did not run this type of scenario (Huppmann et al., 2018).

The following section proposes a process for deriving cost estimates tailored to specific normative choices and further selection criteria.

[346] The IPCC, based on Fuss et al. (2018), finds limits for a sustainable use of both CDR options globally by 2050 to be below 5GtCO_2 p.a. for BECCS and below 3.6GtCO_2 p.a. for sequestration through Afforestation and Reforestation while noting uncertainty in the assessment of sustainable use and economic and technical potential in the latter half of the century.

[347] Moreover, if a sensitivity analysis has not been conducted targeted at assessing the impact of a certain factor of interest, differences in results may also be due to changes in other underlying assumptions.

20 Guidance in four steps to derive climate cost estimates

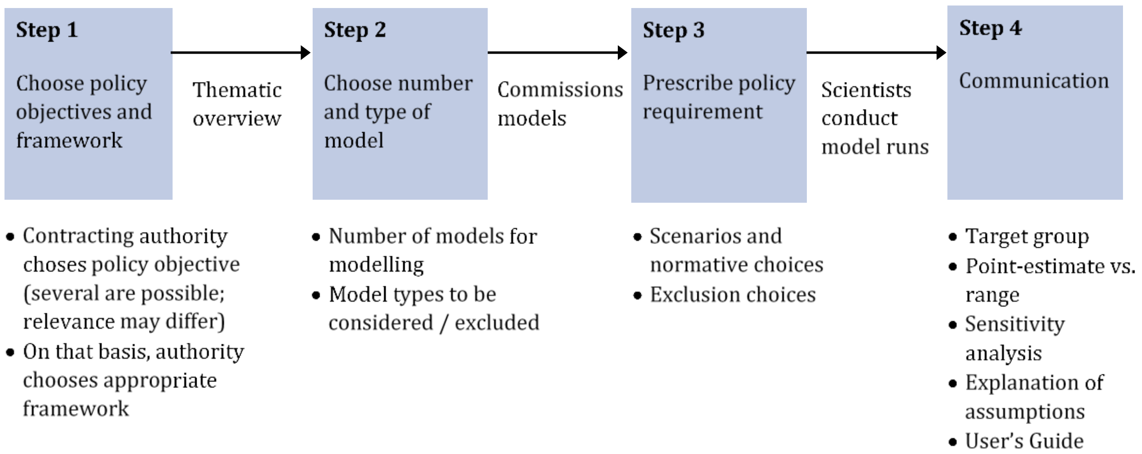
20.1 Overview

In the following, we provide a guidance on the process of deriving climate cost estimates. We will refer to the entity doing so as the contracting authority (or, for brevity, simply "authority"). This is first and foremost a governmental agency, as information on climate costs is an important input or even an independent element of any government's climate policy. A contracting authority may however also be an international organization, an NGO, or a company.

The current literature provides insights and sensitivity analyses on certain influencing factors (e.g. discounting or equity weighting for damage models; exclusion of certain technologies for mitigation models). Yet, many other influencing factors' impacts are less well analysed (e.g. discount rate in mitigation cost models) and the underlying assumptions are often less transparent. It is thus unlikely that the literature allows to derive cost rates that match the contracting authority's specific set of policy requirements — the less so the more requirements there are. In addition, literature results may be outdated with respect to newly available scientific findings, data, scenarios, policies, or prescribed temperature limits. We thus presuppose for the following that the contracting authority commissions tailor-made, up-to-date model results.

We propose to use a four-step process to derive climate costs (see Figure 106). We will explain each of the steps in turn. Note that we strictly focus on the *process* and do not recommend specific values or ranges for the involved parameters or results.

Figure 106: The 4 Steps for a contacting authority to provide information on climate costs



Source: own illustration, Infras

20.2 Step 1: Choose policy objectives and appropriate framework

The contracting authority has to define its policy objective(s) for providing information on climate cost. This a crucial first step as the appropriate framework primarily depends on the objective(s).

Table 42 provides an overview of possible policy objectives, ordered according to the appropriate framework. This is a multiple-choice list. The contracting authority may have several objectives. Nevertheless, we recommend that the authority prioritizes one objective to simplify the analysis in the further steps. We highlighted the policy objectives that are usually of primary political relevance.

Table 42: Policy objectives and the appropriate framework

#	Policy Objective	Comments	Political Relevance
Damage costs are the appropriate framework			
D1	**Raise awareness of climate damages if policy is not acting**	**Related to "costs of inaction"**	**High**
D2	**Internalize external costs according to polluter-pays-principle**	**By means of a tax/levy or other market-based instruments[348]; strong connection to definition of SCC**	**High**
D3	Monetize (avoided) climate damages related to a specific measure or policy instruments	Input to cost-benefit analysis, policy appraisal or regulatory impact assessment[349]	Medium
D4	Determine benefits of a specific adaptation measure	Sector-specific, local damages required[350]	Low
Mitigation costs are the appropriate framework			
M1	**Identify required policy effort (e.g. carbon tax / levy) to remain within a predefined temperature limit**	**The Paris Agreement defines internationally agreed temperature limits**	**High**
M2	Provide a benchmark for socially valuable mitigation measures (private and public) and policy instruments	Corresponds to the French approach (Quinet et al., 2019) ("Social Value of Mitigation Action")	Medium
M3	Assess the (total) costs of reaching a pre-defined mitigation target	To calculate total costs the marginal mitigation costs curve (MAC-curve) or the average mitigation costs are needed	Medium
M4	Assess mitigation costs related to a specific measure or policy instruments	Input to cost-benefit analysis, policy appraisal, or regulatory impact assessment	Medium
Both frameworks may be used			
B1	Provide information for internal shadow pricing of companies	Companies may use both frameworks	Medium
B2	Provide a benchmark value for the price of carbon credits in results-based finance schemes (e.g. Art 6.4)	Price is usually determined by supply and demand; yet, contracting authority may provide benchmark or fix price	Low

Source: own illustration, Infras

[348] Other another market-based instrument may be an emission trading scheme, where emissions are capped. The quantification of climate damages enters only indirectly, e.g. for the decision on price floors and caps.

[349] This may also be done for measures and policy instruments that are not (primarily) targeted towards climate change (e.g. the German transport infrastructure plan ("Bundesverkehrswegeplan"). In such cases, an instrument may also increase climate damages.

[350] For the cost-benefit analysis of a local adaptation measure, the benefits are the sector-specific, local damages (which the adaptation measure partly avoids). SCC, on the contrary, are defined globally and as comprising all sectors. Sector-specific, local damages can only be calculated if explicitly considered in the model.

There are cases where the policy objective(s) does/do not predetermine the framework. First, because the primary policy objective allows for both frameworks (B1 or B2). In this case, we recommend choosing the framework that is deemed to be less uncertain (see Section 19.3). Second, because the contracting authority has various objectives which would demand different frameworks. In this case we recommend providing separate information on damage as well as mitigation costs referring to the respective policy objective (see also Section 20.5). Finally, mitigation costs may serve as an auxiliary proxy for external costs under the circumstances described in the following excursion.

Excursion: Mitigation costs may serve as an auxiliary proxy for external costs

Assume that the main policy objective is to internalize external costs according to polluter-pays-principle (D2). In this case damage costs are usually considered the appropriate framework. The contracting authority may, however, refrain from using damage costs. Either because of its high uncertainty or because the polluter-pays-principle is based on the assumption that the polluter compensates the damaged party, which is hardly feasible in a global and multigenerational setting. If at the same time the contracting authority's jurisdiction is committed to a national carbon budget or emission trajectory, mitigation costs may be used as an auxiliary proxy for external costs, using the following "trigger"-argument:

An additional unit of emitted CO_2 has to be mitigated somewhere else in the economy (or extracted from the air using negative emission technologies) such that the additional unit does not lead to an overall increase in emissions.[351] Therefore, additional emissions trigger additional mitigation but do not cause additional damages. The external costs of CO_2-emission are thus the mitigation cost — either the current mitigation costs (under a trajectory constraint) or the mitigation costs at some unspecified future point in time (under the budget constraint).

Note that this argumentation does <u>not</u> claim that mitigation costs are a proxy for damage costs.

20.3 Step 2: Choose number and type of model

After defining the framework, in a next step the contracting authority ought to choose models to derive climate cost estimates. This choice concerns both the number of models as well as the model-type(s).

20.3.1 Number

To consider structural uncertainty it is best practice for both damage and mitigation costs to consider the results of several models for the further process (model intercomparison). If only one model is used, the contracting authority may be criticized for its specific assumptions. This can be prevented using several models, especially if they are different types. Models may also be used for complementary analysis, e.g. combining insights from detailed (bottom-up) energy system models with macro-economic insights from top-down models.

Using several models does not rule out the possibility that, for communication of climate costs in step 4, only the results of one specific model are being used. For example, if the comparison shows that a model's results and sensitivities with respect to influencing factors are in line with the other models.

[351] The argument is slightly more complex if the emission target is overfulfilled. Yet, also in this case, an additional unit of emission has to be partly compensated, if one follows the logic of full cost accounting and if mitigation is costly (both of which are reasonable assumptions).

20.3.2 Type

For mitigation models, the first decision concerns the choice between global vs. national models. The advantage of global models is that they can convey the 'big picture' of the required global transformation. National models consider national circumstances in more detail (e.g. existing policies, existing industries, potential of renewables, technology costs, social acceptance, and feasibility of certain technologies). In addition, the contracting authority may require or dismiss certain core model characteristics (e.g. partial equilibrium vs. general equilibrium models; computable general equilibrium vs. optimal growths model vs. other non-standard approaches; myopic vs. perfect foresight models). This presupposes that the contracting authority has a clear understanding on the impact and appropriateness of those characteristics. If this is not the case, we recommend using several model types, to account for structural uncertainty. Finally, Stiglitz et al., 2017 provides a blueprint to derive mitigation costs using not only models but also the insights from technological roadmaps as well as national mitigation and development pathways.

For damage cost models the recommendations are analogous. With respect to the model type, especially the way the damage function is constructed is relevant. The contracting authority may require or dismiss sectoral enumeration, an aggregate damage function or functions based on macro-econometric studies. Instead of purely relying on models, one may also consider expert elicitation approaches, as for example conducted by Pindyck, 2019 (see Section 14).

20.4 Step 3: Prescribe policy requirements

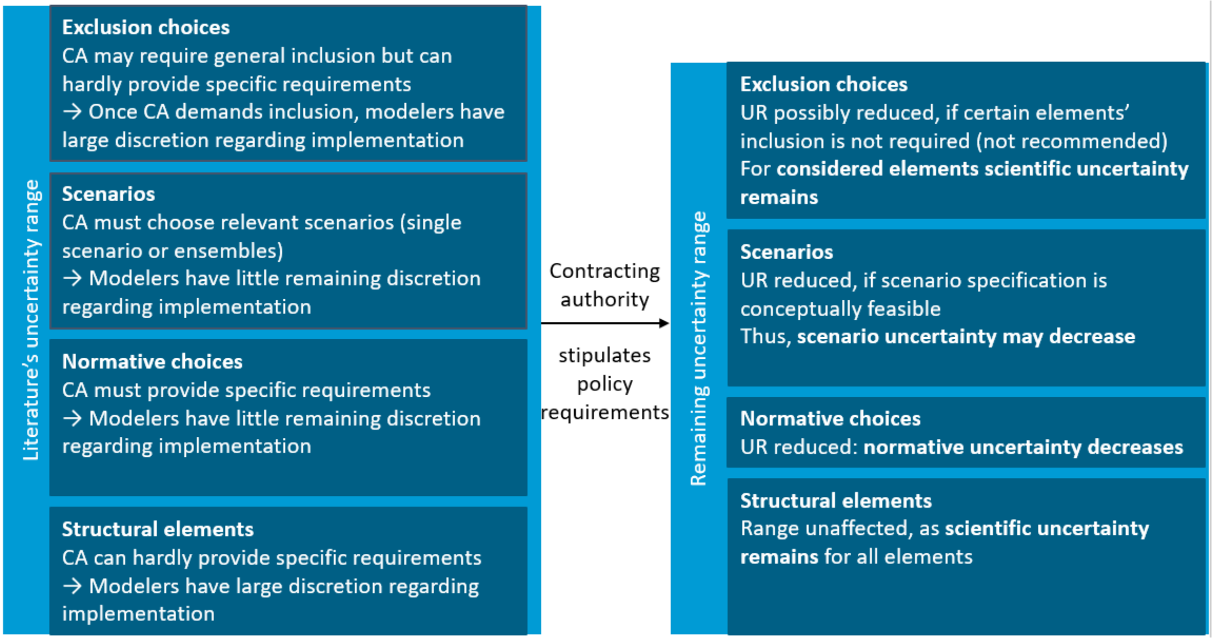
20.4.1 Policy requirements on influencing factors

This chapter heavily builds on the categorization of influencing factors in Section 19.2 as well as on the uncertainty types as defined in Section 2.3.3. We recommend reading these sections first.

In this third step the contracting authority prescribes policy requirements. Figure 107 illustrates that this is only possible for certain categories of influencing factors: The authority can prescribe normative choices with respect to parameters (e.g. inequality aversion), schemes (e.g. discounting scheme), or constraints (e.g. whether to restrict the deployment of BECCS). Furthermore, it can decide which exclusion choices to exclude (or include) and possibly choose certain scenarios. The contracting authority's policy requirements thus decreases the literature's uncertainty range — which stems from all four categories — to a certain extent (see also the example in Section 19.5). The remaining uncertainty range primarily stems from scientific (related to essential and exclusion choices) and scenario uncertainty.

Note that the uncertainty range may be further reduced if one does not implement influencing factors related to exclusion choices in the model (see Section 19.2.4), as this "hides" the scientific uncertainty introduced by those elements. However, this is only a pseudo-gain: the corresponding uncertainty has been merely neglected. For that reason, we strongly recommend considering all exclusion choices.

Figure 107: Impact of policy requirements on uncertainty range



Legend: CA: Contracting Authority; UR: Uncertainty Range
Source: own illustration, Infras

Furthermore, we recommend the following:

- Derive the normative choices in a separate sub-process considering all relevant stakeholders of the contracting authority and the considered policy objective. Explicitly consider and discuss all possible policy requirements and define which aspects should be subject to sensitivity analyses.
- Consider various forms of uncertainty
  - To account for parametric uncertainty, use Monte Carlo methods with parametric equations and a suitable range of input parameters
  - To account for structural uncertainty, use several models
  - If appropriate, use several scenarios (see Section 20.4.2 and especially Table 43).
- Also consider explicitly the policy requirements that determine the changing climate costs with time.
- If the final communication is supposed to present a sensitivity analysis, it will be necessary to define several sets of policy requirements.

As noted already in Section 19.2, the categorization of influencing factors is sometimes blurred, especially between normative choices and scientific uncertainty. A more in-depth approach by the contracting authority will increase the potential to prescribe policy requirements, as certain scientific aspects reveal themselves as value judgments upon a closer look. Therefore, this guidance is not meant to be a final blueprint, but rather serves to allude to the contracting authority's potential choices. It is in the end the task of the authority to decide on the amount and depth of the policy requirements they want to prescribe upon the models.

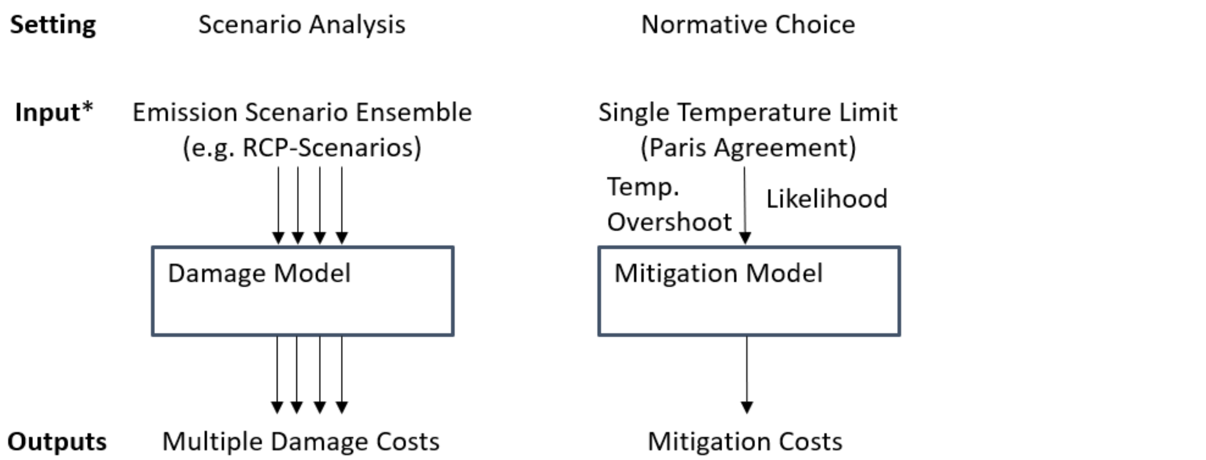
20.4.2 Special consideration on emission scenarios and temperature limits

Future climate policy and thus emissions are unpredictable. This has different implications for the two frameworks:

- For **damage models** it is best practice to use **emission scenario ensembles** as inputs. To provide a meaningful estimate of climate damages, it is inevitable to consider a wide set of possible future realizations.
- **Mitigation models,** on the other hand, use a single target as input in the sense of a normative choice.[352] This is because mitigation models are built to answer research questions related to ways and costs of obeying to a predefined mitigation target. In recent years, almost all models used the **temperature limit** provided by the Paris Agreement for that purpose (though with different assumptions on the temporary temperature overshoot and the likelihood of reaching the limit).

This difference is shown in Figure 108.[353]

Figure 108: Emissions and temperature as inputs of the respective frameworks



*For simplification, this illustration does not consider other influencing factors (that is all other input to models) but focuses on emission scenarios or temperature limits, respectively.

Source: own illustration, Infras

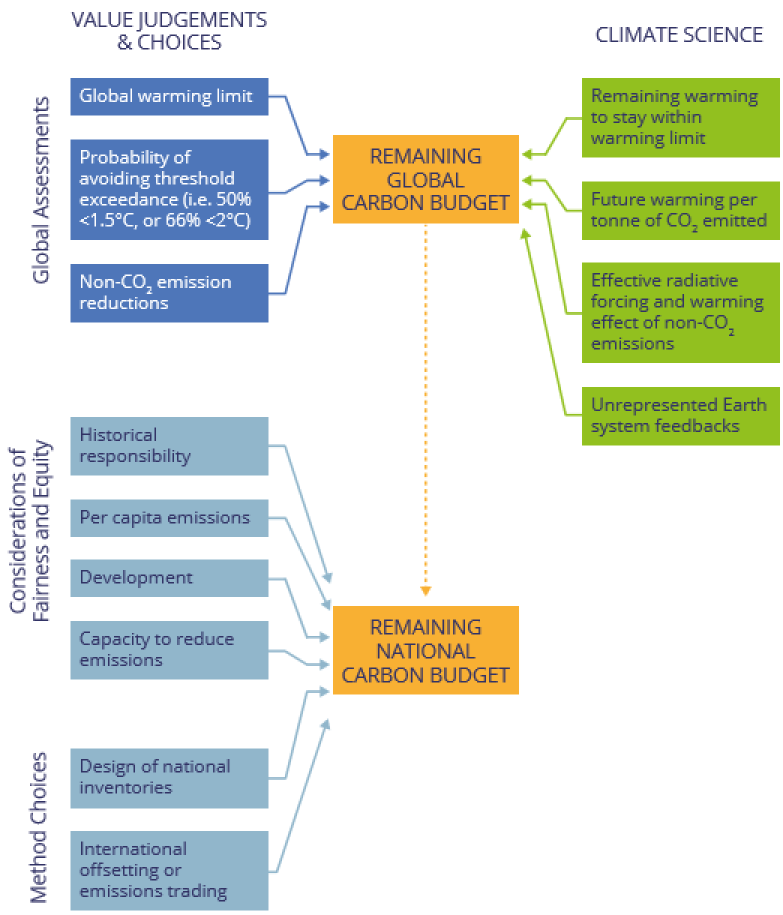
For mitigation costs, the most target most relevant for policy is derived from the Paris Agreement, where countries have agreed upon a temperature limit of well below 2°C and pursuing efforts to limit it to 1.5°C. This choice has been guided by climate science rather than economic models. But translating the wording of the Paris Agreement in a specific model input is not straightforward. The wording "well-below" has to be quantified and either 2°C or 1.5°C may be chosen as the limit. Furthermore, the chosen limit must be coupled with (1) specifications on

[352] In some studies, models run the same analysis for two or three different temperature limits to assess the impact for different ambition levels.

[353] Not shown is that cost-benefit models do not need any emission scenarios or temperature limit as input. Instead, these variables are derived within the model to balance costs and benefits in a setting of economic optimization.

the acceptable temporary temperature (or carbon budget) overshoot[354] until the time the limit is reached and (2) on the likelihood of remaining below the limit. Another way of translating the Paris Agreement into model input builds upon the fact that it basically implies an emission trajectory that reaches net-zero emissions by 2030 to 2050. This is the approach taken by most national mitigation models (national emissions alone have limited impact on the temperature increases), but it may also be used for global models. National models may also use a national carbon budget. This requires allocating the global budget to nations (regional burden sharing), which is yet another normative choice. These aspects are summarized in Figure 109.

Figure 109: From a temperature limit to a global carbon budget to a national carbon budget



Source: CONSTRAIN project Annual Report 2019 (Nauels, Rosen, Mauritsen, et al., 2019), Figure 2.

For damage costs in connection with the policy objective to determine external costs, there is no such salient choice. It is essential to consider the impacts of a wide range of potential future emission trajectories, as future emissions are not predictable. It is thus best-practice to use an ensemble of emission scenarios (e.g. RCP-scenarios) in the sense of several "what-if" analyses — without any probability attached to a single outcome. This results in several cost estimates, even neglecting all other types of uncertainties.

If the policy objective of providing damage cost estimates is "raise awareness of climate damages if policy is not acting" it is sensible to use a single scenario with high emissions (that is

[354] The issue of overshoot mainly applies to 1.5°C targets and less to 2°C targets.

a scenario with low policy ambition). This is a normative choice directly related to the wording "if policy is not acting".

Note that, technically, both mitigation and damage models can use emission scenarios, GHG concentrations, carbon budgets, or temperature limits as inputs. For mitigation models, the recent focus on temperature limits is because mitigation's communication is aligned with the Paris Agreement (e.g. a current IPCC special report which relies heavily on mitigation cost models is called "Global Warming of 1.5 ºC"). Damage cost models on the other hand use emission scenarios in order to increase comparability of results and for historical reasons.[355] The resulting temperature trajectories are usually displayed as additional information.

Table 43 summarizes our recommendations with respect to emission scenarios and temperature limits.

Table 43: Recommended use of emission scenarios and temperature limits

Framework	Recommendation	Setting
Damage costs — external costs and others	Use multiple emission scenarios covering the full range of plausible futures if the primary policy objective is "Internalize external costs according to polluter-pays-principle" (D2 in Table 42) and also if the policy objectives are D3 or D4.	Scenario analysis
Damage costs — costs of inaction	Use scenario with current policy ambition, if the primary policy objective is "Raise awareness of climate damages if policy is not acting" (D1 in Table 42)	Normative choice

Mitigation cost	• Use single temperature limit in line with the Paris Agreement
	• In addition, provide specifications on
	  ○ acceptable temporary temperature overshoot
	  ○ likelihood of remaining within temperature limit
		Normative choice

Endogenous costs	• Not recommended to use this framework (see Box 2) • For information: Endogenous costs models do not need such input, as emissions and temperature are determined within the model	Economic Optimization

Source: own illustration, Infras

20.4.3 Commission model runs

As already described in Section 20.1, we recommend that the contracting authority commissions tailor-made, up-to-date model results — which entails providing the necessary funding. For adjustments related to scenarios and single parameters (normative choices), expenses may be moderate (e.g. using Mimi-versions of damage models). More fundamental changes are likely to be more expensive (e.g. changing or adding sectors in damage models or adjusting technology options in mitigation models).

The prescription of policy requirements may occur in two phases. First, the overall framework and the core requirements are prescribed. Second, more specific requirements are prescribed, as

[355] Using emissions scenarios for damage models increases comparability, as (1) this does not require the translation from temperature targets to emissions trajectories (which is complex and thus introduces uncertainties); (2) Emission scenarios are the inputs of choice for dedicated climate models to which damage models share a close connection; (3) Emission scenarios have been the common procedure in the 1990s when damage models have been devised.

the contracting authority acquires a deeper understanding of the modelling parameters, model implementation details and choices during the process.

To consider the fact that mitigation models run into infeasibility issues for certain (less optimistic) assumptions (see also Section 19.5), we recommend to also collect information on which models have *not* been able to produce results and report and evaluate this information qualitatively.

20.5 Step 4: Communication

In the final step, the contracting authority uses the model results to finally provide estimates on climate costs. For communication, there is the fundamental tradeoff between simplicity and scientific comprehensiveness. This tradeoff arises related to several aspect. First, the climate costs may be provided as a point estimate or as a range. The respective advantages and disadvantages are depicted in Table 44. In both cases, the contracting authority may have to condense the model results (to a single point in the former case or to an upper and lower bound in the latter case). If, on the other hand, only a single deterministic model result is available (e.g. from a single mitigation model), there is no proper basis to determine a range.

Second, for simplified communication (e.g. to the general media), a single "best-fit" climate cost estimate may be provided based on the most relevant policy objective and best-guess set of policy requirement. Sophisticated users may be addressed by also providing several estimates for different combinations of policy objectives and sets of policy requirements (sensitivity analyses). This would entail providing separate estimates for damage costs and mitigation costs. To guide the user, a flowchart may be in order.

Table 44: Communication: point estimate vs. range

Range	Point Estimate
Advantages	
- Reflects the underlying uncertainty - Allows sophisticated user a proper uncertainty analysis	- Straightforward to use - Eases communication with lay-people
Disadvantages	
- Allows pick-and-choose - Communication more complex - There are various ways and wordings to present ranges (including best guess, central value, sensitivity analysis, likelihood of range) - Contracting authority may still have to pick an upper and lower bound	- Uncertainty not properly accounted for - No sensitivity analysis possible - Requires the contracting authority to choose a certain point, opening the door for criticism

Source: own illustration, Infras

Especially for damage cost estimates, several factors are difficult if not impossible to monetize (e.g. non-market impacts or catastrophic climate change). A way to deal with this is to explicitly *not* consider these aspects for modelling and mark the results as a lower bound, supplemented by a qualitative description of the missing elements. Even though such an approach is scientifically meaningful, for communication in this context it is problematic: Users of climate costs estimates are usually mainly interested in the number and may have difficulties to consider the strings attached in their analysis.

Climate costs change with time and thus a trajectory of carbon prices has to be provided.[356] To facilitate proper use, this information should be presented in a figure as well as in a table that depicts the climate costs for each year up to 2050. This has been done for example in World Bank, 2017.

It is good practice that the contracting authority updates the recommendations in regular intervals. In these updates, all the process steps should be repeated, starting with a literature reviewed on new findings, results, and empirical data. This may justify increasing or decreasing the recommended climate costs. To guarantee consistency, the conceptual and normative basis should only be changed if there are convincing reasons. Note that especially for mitigation cost estimates, the remaining carbon budget for a certain temperature limit is highly relevant for updates. If the carbon budget has been overused in the last period, the mitigation costs will have to be adjusted upward and vice versa.[357] In addition, prices have to be adjusted for inflation as part of the update.

Finally, the caveats as discussed in Section 19.4 should be kept in mind when communicating results.

[356] This has been done by all stakeholders presented as examples in Section 3.

[357] Note that the mitigation costs increase with time as mitigation is increasingly more costly. The mentioned adjustment refers to adjusting this upward-sloping curve.

A Glossary

Name	Description
Assumption	In a narrow sense the choice of the value of an influencing factor (e.g. pure rate of time preference = 1%). In the wider sense related to all choices that influence the results (e.g. choice of the approach to set up the damage function).
Base year	Costs incurred in the future can be calibrated either to a fixed base year or to the respective year of emission. These two costs are not directly comparable.
Business-as-usual emissions (BAU)	This is the level of emissions without climate policy (sometimes also "with current climate policy"). It depends on assumptions about *economic growth*, greenhouse gas intensity, (autonomous) *technological progress*, *population growth*, etc. Therefore, there is a broad spectrum.
Carbon budget	The carbon budget arises from the fact that cumulative emissions determine climate change — and not the distribution those emissions within time. see also *Emission target*?
Carbon cycle	After anthropogenic CO_2 has been emitted into the atmosphere, it becomes part of the natural carbon cycle that includes various sources and sinks on very different time scales. Roughly half of the anthropogenic CO_2 stays in the atmosphere on short to medium time scales, the other half is taken up by the upper ocean and the biosphere.
Climate impacts	Biophysical or social effects driven by climate change (e.g. changes in land productivity, mortality, morbidity, water supply, coastal flooding, or conflict)
Climate damages	Monetized estimates of the climate impacts. May be expressed as marginal (see also *social cost of carbon),* average or total costs.
Co-benefits	Benefits apart from reduced climate change that arise due to mitigation approaches (e.g. reduced NO_x or particulate matter emissions when switching from fossil to electric cars). The *net costs* of mitigation are correspondingly the mitigation cost subtracted by the co-benefits.
Consumption	Consumption refers to the value of all goods and services consumed by households. Some of these may be purchased in markets, and thus constitute part of GDP, while others (e.g., good health, ecosystem services) are not generally traded in markets.
Contracting authority	A governmental or non-governmental entity that aims at providing information on climate costs and for that reason commissions a third party for modelling.
Climate sensitivity	The equilibrium climate sensitivity (ECS) describes the change in the global average temperature due to an increase in greenhouse gas emissions in the sense of a proportionality constant. It measures the long-term response of global mean temperature increase for a doubling of CO2 concentrations from their preindustrial levels.
Damages costs	See *climate damages.*
Decision making objectives	see *Policy Objective*
Discount rate	A parameter to quantify the importance of future costs. Plays a fundamental role in the assessment of future costs and benefits in the field of climate change due to the long time-periods to be considered. Even small differences have a strong impact on cost estimates. There are three common discounting schemes: • A fixed discount rate, • A predefined declining discount rate,

Name	Description
	• Ramsey Discounting. It combines several reasons for discounting (pure time discounting, inequality aversion, economic growth and in some cases risk aversion). Ramsey Discounting usually also results in a declining discount rate as it is assumed that economic growth slows down with time.
Economic growth	Assumptions about future economic growth (global and regional) and thus the prosperity of future generations play an important role because they influence other influencing factors (e.g. discount rate, equity weighting or business-as-usual emissions).
Emission target	Usually defined as an emission path over time, a stable atmospheric CO2 concentration at some point in time or linked to a temperature target. For the latter, the concept of the global carbon budget has been introduced, because quasi irreversible warming correlates with the total amount of CO2 emitted (Meinshausen, 2009). The carbon budget can also be used to derive country-specific GHG budgets, even if there is no consensus on an appropriate mechanism yet.
Gross domestic product (GDP)	GDP represents the value of all goods and services produced by a country and explicitly or implicitly sold in markets within a certain time period (usually one year)
Global warming potential GWP	see *Greenhouse* gases *other than CO2.*
Greenhouse gases other than CO_2 (non-CO_2 GHG)	Mainly methane (CH4), nitrous oxide (N2O), and fluorinated gases (hydrofluorocarbons, perfluorocarbons or sulphur hexafluoride). They are relevant for both damage and mitigation cost estimates. For damage costs it is common practice to compare the impact of other greenhouse gases based on their warming potential over a period of 100 years as compare to CO_2 (global warming potential GWP). The GWP is strongly dependent on this *time-horizon*. This should therefore correspond to the general time-horizon of the study. CO_2 mitigation is mostly related to energy generation, while other greenhouse gases are often generated by other processes (agriculture, waste, etc.). The respective abatement costs and the potential are thus different. It therefore influences cost estimates whether and how additional greenhouse gases are considered (see Strefler et al 2014).
Inequality aversion	Expresses the extent to which it is preferred to give an equal amount, e.g. money, to a less wealthy person or society. One usually assumes that the future is richer (due to *economic growth*), so that under inequality aversion in the present, the damages of the future have less weight than those of the present (intertemporal). On the other hand, climate change mainly affects the poor, so that their damage has a greater weight under inequality aversion. Such an intratemporal weighting is called *equity weighting* (Fankhauser 1997).
Influencing factor	Feature that has an impact on the results. There are a large variety of influencing factors (e.g. technical progress, pure rate of time preference). Closely related to assumptions
Instruments	A policy related to mitigation or adaptation, such as a tax, a regulation or a law.
Integrated Assessment models (IAM)	Numerical models related to the analysis of a broad variety of aspects of climate change. They are being used to model climate damages as well as mitigation costs.
Measures	Specific mitigation investment into e.g. energy efficiency or renewable energy.
Mitigation Costs	Consist mainly of technology costs (i.e. investment costs) but may also include other type of costs (e.g. administrative costs).

Name	Description
Net mitigation costs	They are the *mitigation* cost subtracted by the *co-benefits*.
Policy objective	The aim of policy makers using the cost estimates. Policy objective are related to damage or mitigation costs. If a broad set of users is referred to (i.e. in addition to policy makers also NGOs, civil society, businesses, etc.) the broader term decision making objectives is used.
Population size	Plays an important role in a utilitarian setting because global damage is seen as the sum of individual damage. Therefore, deviating population forecasts strongly change results. Predictions of population trends also play a major role in calculating future GHG emissions.
Purchasing power Parity	Claims about the welfare people get from their incomes should be adjusted for purchasing power because people get welfare from consumption, and consumption is purchased at the prices paid in their country of residence. Since at market exchange rates a large number of non-tradable goods are relatively less expensive in developing countries, using nominal or market exchange rates would overstate the (current) degree of inequality between countries compared to the measurements using PPPs.
Pure rate of time preference (PRTP)	Expresses how strongly future well-being (of the same or future generations) is taken into account. A value of 0% means that everything is weighted equally until the end of the *time-horizon* under consideration. A value greater than 0% accordingly means that the future is weighted less strongly. In most cases a fixed annual discount rate is chosen. However, many experts consider a discount rate that decreases over time to be more appropriate (following the argument of Weitzman 1998).
Policy requirements	Set of assumption the contracting authority prescribes for climate cost modelling.
Research Question	The aim of a certain study. Most often the research question relates to improving or refining cost estimates. In addition, a study may or may not explicitly address *policy objectives*.
Risk aversion	An actor with a risk aversion prefers a certain result to an uncertain one with the same expected value. In economic models, risk aversion is often described with the same parameters and model approach as the *inequality aversion* but note that the underlying definitions are not the same.
Social Costs of Carbon (SCC)	Estimates the monetized change in social welfare over all future time periods from emitting one additional tone of carbon today, conditional on a specific trajectory of future global emissions and economic and population growth. SCC are thus marginal costs. They are often used a synonym for *damage costs* or *climate damages.*
Social costs /benefits	Private costs plus the external costs to society using a certain product. In the case of using a product that entails emissions of greenhouse gas emissions (cars), external costs are due to the social costs of carbon but also due to e.g. local air pollution or noise. Social costs/benefits may in addition include further aspects such as impact on inequality within regions/countries.
Technical progress	Has a big influence on the future costs of mitigation technologies. In the first economic models, it was usually assumed to be exogenous. Currently, technical progress is often modelled endogenously, i.e. dependent on climate policies. Technical progress is often linked to socio-economic scenarios.
Time-horizon	The consequences of climate change manifest themselves only in the medium to long-term, sometimes also in the very long term (e.g. rising sea levels, melting of ice sheets,

Name	Description
	etc.). Whether (very) long-term costs are also considered has an influence, if the chosen discount rate is low.
Transient climate response (TCR)	Is the temperature increases if CO2-concentrations are being raised at 1 percent per year until concentrations double (which occurs in after 70 years).
Welfare	the well-being actors derive from consumption of goods and services. Often also called utility.

B Climate Costs in various countries

The following table shows the costs rate of various countries as provided by the original sources. For the overview in Section 3.7, we normalized these values to €2019 values.

Table 45: Costs rates in various countries as given by original sources

Country	Assumption / Setting	Frame-work	Unit	Carbon Price 2020	2030	2050	Reference
UK	Non EU-ETS	Mitigation	£2000	16 (8-24)	19 (10-29)	55 (27-82)	UK 2009
UK	EU-ETS	Mitigation	£2018	14 (0-28)	81 (40-121)	NA	UK 2019
France		Mitigation	€2018	84	250	775	FR 2019
US	Before Trump-Adm.	SCC	$2007	42 (12–123	50 (16–152)	69 (26–212)	IAWG 2016
Germany	PRTP=1%	SCC	€2016	180	205	240	UBA 2018
Germany	PRTP=0%	SCC	€2016	640	670	730	UBA 2018
European Investment Bank	Unclear	Unclear	€2015	45 (20–70)	52 (25–90)	120 (55–230)	EIB 2015
World Bank		Mitigation	$2017	40–80	50–100	78–156	WB 2017

Source: own illustration, Infras. Data: see references

C Econometric methods in estimating damage costs

C.1 Theoretical background

Econometric approaches are interested in isolating the effect of climate on a particular dependent variable, such as a measured economic activity (e.g., GDP, etc.), sectoral value-added, or a socioeconomic measurement (e.g., growth per capita, poverty, or health). In order to do this, econometric regressions estimate the average (statistically significant) change to the dependent variable for every unit change in the climate variable over a specific period of time and space.

The basic, overarching functional form used in climate econometrics is given by the equation by (Dell, Jones, & Olken, 2014) below, which states that the dependent variable or the outcome variable of interest, *Y*, is a function of a set of independent variables composed of climatic variables, C, and other variables, X.

$$Y = f(C, X)$$

C represents different climate variables such as temperature, precipitation, wind, humidity, and/or a combination of these variables that capture ambient temperature and extreme events (e.g., Wet Bulb Globe Temperature, SPI, SPEI, RX5d). The functional form *f* of the equation and how *C* is specified is critical in describing the relationship between climate and the economy.

X is a set of control variables that includes all other variables that are correlated with *C* and affect *Y*. The choice of control variables can affect the estimate of the coefficient of the climate variable of interest in *C*, particularly in two opposing ways: (1) failure to control for a variable that is correlated with *C* and affects *Y* results in an omitted variable bias, or the opposite – (2) if there is an over-specification problem, wherein X is an outcome of C, the resulting coefficient of C will not reflect the net effect of C on Y. As a best practice to avoid the over-specification problem, a rule of thumb is to only include credibly exogenous regressors (e.g., external price shocks for a small economy; other weather variables not in C); and only include potentially endogenous control variables if there is strong evidence that it is not affected by the climate variable of interest (Dell et al., 2014).

In a multivariate regression model such as the one above, the coefficients represent the partial effect of the independent variable to the dependent variable, holding all other variables constant.

The resulting marginal effect of climate to the outcome of interest, holding other factors constant, captures two impacts: (1) the direct effect, which is the immediate impact (e.g., high precipitation causes large amounts of rainfall and makes the ground wet) and is likely to be a prominent impact for economic activities that are highly exposed and dependent on climate (e.g., rainfed agriculture, renewable energy sources, etc.); (2) indirect effect that results from an alteration in outcomes based on reactions ex-ante or ex-post to the occurrence of the direct effect. One of the indirect effects is the "belief effect", which is how the perception of individuals towards climate affect their decisions and resulting outcomes (S. Hsiang, 2016). Another is the "trade effect" (Stephan & Schenker, 2012), by which, in the short-run, loss in domestic production results in changes in imports and the terms-of-trade (that is the ratio of an index of export prices to an index of import prices). Indirect effect is particularly important for measuring the impacts of adaptation and coping behaviors.

For a general review on climate econometrics see (S. Hsiang, 2016).

C.2 Cross-sectional methods

Cross-sectional methods use data from a sample of several entities such as geographical area, individuals, groups, etc., at a single time reference point (Wooldridge, 2013). Because there is only one data point for each spatial entity, the method encounters the Fundamental Problem of Causal Inference (Holland, 1986), as the counterfactuals, or the alternative climate in a given location and time, are unobserved. To resolve this problem, econometric methods assume unit homogeneity. That is, for two locations with identical characteristics, the difference in outcome is the inferred impact from the difference in the climate of the two locations at a given point in time.

Cross-sectional analyses serve two purposes in climate econometrics: first, to highlight spatial differences at a point in time (e.g., global dataset in 2020); and second, to estimate long-run impacts of climate to the outcome variable, such that the observation for each location reflect the average of a long time series (e.g., global dataset containing the average GDP growth from 1960-2020).

An example of a cross-sectional study is (Nordhaus, 2006), which investigated the impact of geography to the macroeconomy of large countries. Through the G-Econ project, Nordhaus (2006) developed the concept of Gross Cell Product (GCP), which is essentially a 1°x1° gridded[358] extrapolation of GDP to better match geographic and climatic data. The GCP dataset has output estimates for a total of 25,572 terrestrial cells Nordhaus (2006) uses a multivariate regression with the logarithm of output per square kilometer as dependent variable and as independent variables the mean annual temperature and mean annual precipitation (and controls for mean elevation, roughness, soil category, and distance from the coastline). He finds evidence evi of a "climate-output reversal", wherein the relationship between temperature and economic output is negative and highly non-linear when measured on a per capita basis[359], and positive when measured per area. Nordhaus (2006) hypothesizes that this paradox is caused by the following possible reasons: (1) the mobility of factors -- people are mobile, while land is fixed – such that areal productivity is relatively fixed, while labor productivity is not; (2) lower temperatures tend to have high output per capita due to the capital-intensive nature of activities, and (3) in relation to the second point, that economies in colder regions have generally higher per capita output than most high-temperature regions.

An example of a long-run impact analysis using cross-sectional regressions is the study by (Dell, Jones, & Olken, 2009) with the data averaged over the period 1950-2000 for 134 countries. Results show that per capita income is reduced by 8.5 percent for every degree increase in temperature. Furthermore, poorer countries are already having hotter climates, and will likely suffer severe damages from climate change in the future.

Causative effects are difficult to establish in cross-sectional studies, mainly because the variation in climates across geographical locations are largely fixed and some responses of the dependent variable may be the result of very long-run mechanisms that cannot be isolated in a cross-sectional study (e.g., impact on climate on institutions before and after colonialism), therefore it is difficult to identify the economic impacts that are solely related to the current climate (Dell et al., 2014). Furthermore, cross-sectional analysis is particularly vulnerable to omitted variable

[358] A 1° × 1° grid cell is approximately 111×111 km² at the equator. Latitudinal distances remain about constant, while a degree of longitude is widest at the equator and gradually shrinks to zero at the poles due to the convergence of the meridians (Sources: USNA website https://www.usna.edu/Users/oceano/pguth/md_help/html/approx_equivalents.htm; and USGS website https://www.usgs.gov/faqs/how-much-distance-does-a-degree-minute-and-second-cover-your-maps?qt-news_science_products=0#qt-news_science_products).

[359] Particularly, output per capita increases as the distance to the equator increases.

bias (Wooldridge, 2002). There is thus no certainty that the results are unbiased. In fields that are already heavily researched, past publications can provide however a general confidence that all important variables have been included (S. Hsiang, 2016).

C.3 Panel methods

Panel methods use time series data for each of the cross-sectional entities in the sample (Wooldridge, 2013). Panel methods are common in climate econometrics to estimate short-run impacts across many countries/regions over a long period of time with high frequency (e.g., annual), thereby maximizing the number of observations in the regression. Panel methods improve the establishment of causality (compared to the cross-sectional method), such that the resulting estimates can provide information on (1) the impact of a weather shock, depending on the locations' normal climate, (2) the change in the dependent variable given a change in the climate shock to the same location over time, thus minimizing the risk of an omitted variable bias from time-invariant factors.

Recent panel regression models often use a reduced form climate-economy equation, which has two advantages: (1) it makes few assumptions on identifying variables to include, and (2) it still allows for strong causative interpretation. An example is the fixed effects method, which includes a variable to capture all time-invariant, area-specific characteristics (e.g., geographical characteristics); and a time fixed effect, which captures events common to all spatial entities at a given point in time (e.g., global crisis year). Applying this to panel data avoids the risk of an omitted variable bias and over-specification problems (or the inclusion of too many variables). This method has been used for global studies, as well as sub-national studies by authors such as (Burke et al., 2015; Dell, Jones, & Olken, 2012; IMF, 2017; Pretis et al., 2018).

Whether estimates from short-run historical responses can be applied to climate projections or the possibility of adaptation is matter of debate among scholars. "[A]ssessments superimpose biophysical 'futures' onto present-day socioeconomic conditions" (IPCC AR5), which may thus produce an overestimation of impacts. This is a "highly unsatisfactory, if not outright, misleading approach" (Lutz & Muttarak, 2017).

The studies on panel data methods have been extensively reviewed by (Dell et al., 2014), which also includes the different types of climate data used in these analyses.

C.4 Short-run vs long-run impacts and implications for adaptation

The short-run and long-run equilibrium in economic theories — or the point at which demand and supply meet — rely heavily on the assumed time-scale needed for institutions and inputs to adjust to specific shocks (Mayer, 1974). For instance, in the short-run, institutions are assumed to be fixed and labour or capital is immobile. However, in the long-run, institutions can be established or capital and labour migrate from one location or industry to another. As a consequence, in the models there is full employment with all factors of production being optimally used.

Following the same train of thought, short-run climate shocks are likely have less impact in the long-run, when the factors of production have had enough time to adapt to changes (e.g., a short-run agricultural loss will likely trigger innovation (irrigation, different types of plants) or structural transformation in the long-run). On the other hand, short-run adaptation measures may not be applicable in the long-run for repeated climate shock (e.g., irrigation may not be applicable if in the long-run, the supply of water is largely depleted due to an increasing incidence and duration of droughts). Finally, consumer will also change demand in response to shocks. (Dell et al., 2014; Fankhauser, 2017)

In the following, we describe three different approaches that serve to quantify adaptation. They are based on the difference in the impact between two different points in time (start and end of the sample period) or two different time scales (e.g., short vs long-run) given the same exposure to climate change. While the approaches explicitly aim to describe adaptation, conceptually they also capture the effects from the intensification of climate, and general equilibrium changes (e.g., reallocation of resources over time and space that would result in lower impacts, given the same intensity of climate).

C.4.1 Difference between short-run and long-run impacts

This approach estimates short-run impact using annual variations. The long-run impact is captured in two ways: (1) using a cross-sectional analysis on decades-long averages of datasets, and (2) by estimating the impact of the weather on economic growth, rather than on GDP levels as in (Dell et al., 2012) to arrive at a persistent, more lasting impact. Assuming that some of the short-run effects are reduced through adaptation in the long-run (Dell et al., 2009), the degree of adaptation is the difference between the estimated long-run effect — controlling for an (exogenously-determined) rate of convergence[360] — and the estimated short-run effect.

C.4.2 Long-differences approach

The long differences approach aims to capture long-run impacts of climate by averaging a number of years around the start of the period and the end of the period, and then taking the difference of the two averages. It is considered a hybrid of time series and cross-sectional methods (Hsiang, 2016), which has an advantage over panel methods because it quantifies long-run impacts, and an advantage over cross-section approach by avoiding concerns over the omitted variable bias (Burke & Emerick, 2016). The approach is essentially a cross-section comparison of impacts over time in a specified length of time and can be related to adaptation by comparing the resulting coefficients between two time periods (e.g., time periods of different lengths, or long time periods succeeding each other). Studies that have used this method are (Dell et al., 2012; and Burke & Emerick, 2016), which have looked into the effects of climate on growth, crop yields, and conflict.

C.4.3 Rolling averages

The rolling averages approach takes a rolling window average of a set number of years that is less than the total sample size (e.g., 10 or 15-year window over a total 60-year period), and compares the relationship between climate and the averaged dependent variable of interest over time. An example of this is the analysis from the (IMF, 2017), which resulted in no evidence of adaptation over a 20-year rolling window, since the relationship between temperature and per capita output has remained constant.

[360] The rate of convergence is not endogenously determined within the model but is referenced to previous studies of Barro and Salai-Martin (1995), Francesco Caselli, Gerardo Esquivel, and Fernando Lefort (1996), which estimates a convergence rate of between 0.02 and 0.10. Convergence refers to the natural tendency of poorer countries to have higher growth rates than richer countries, therefore leading to income per capita to move closer together at some point in time.

D Appendix on Part 3 Mitigation Cost

D.1 Introduction to selected models for assessing long-term transformation pathways

AIM

The Asia-Pacific Integrated Model (AIM) is a global, multi-regional, integrated assessment model developed by the National Institute for Environmental Studies (NIES) in collaboration with Kyoto University, Mizuho Information and Research Institute and several research institutes in the Asia-Pacific region (http://www-iam.nies.go.jp/aim/). The model characteristics are described in more detail in this book chapter by Kainuma and co-authors (2003) about the model.

AIM is comprised of three key modules:

- the greenhouse gas (GHG) emission model (AIM/emission)
- the global climate change model (AIM/climate) and
- the climate change impact model (AIM/impact).

The AIM/emission model estimates GHG emissions and is applied to assess impacts of various mitigation policies. It integrates bottom-up national modules with top-down global modules.

The AIM/climate model estimates concentrations of greenhouse gases and quantifies the global mean temperature increase. The AIM/impact model estimates climate change impacts on the natural environment and socio-economy of the Asian-Pacific region.

A key characteristic of AIM is its focus on the Asian region, including Japan, China, India, Korea, Thailand, Malaysia and Vietnam (Kainuma et al., 2003).

DNE-21+

The Dynamic New Earth 21 plus (DNE21+) model has been developed by the Research Institute of Innovative Technology for the Earth (RITE), Japan. This global model is divided into 50 regions. The energy system model is a bottom-up, linear programming model, minimizing total costs of energy systems. In addition to CO_2 emissions from the energy sector, DNE21+ also covers non-energy CO_2 and non-CO_2 emissions. The non-CO_2 GHG model is a proxy model using elasticities that represent bottom-up assessments of mitigation technologies performed by USEPA. Further in-depth description of model characteristics and fundamentals is provided at https://www.rite.or.jp/system/en/research/new-earth/dne21-model-outline/.

E3MG/E3ME

E3MG was originally developed through the European Commission's research framework programmes and is now widely used globally for policy assessment, for forecasting and for research purposes.

E3MG explicitly accounts for a relatively wide range of low-carbon technologies which are integrated within a top-down framework involving the use of econometric estimation to capture historical behaviour and the effects of endogenous technological change at the macro-level. E3MG is a non-equilibrium model implying that labour, foreign exchange and financial markets do not necessarily clear but have deficits or surpluses in open economies depending on the year and region. A bottom-up energy system module covers modelling of 28 different energy technologies. This hybrid approach allows for the modelling of the interactions between the economy, energy system, and impacts on anthropogenic emissions.

The European version (E3ME) combines the previous model version with a new global database to cover Europe at Member State level plus Norway and Switzerland. The three model components or modules consist of: energy, environment and economy. The economy module quantifies the economic activity and general price levels as input to the energy module; the energy module determines energy consumption levels and energy prices as a feedback to the macroeconomic module as well as input to the emissions module. For further description of the model please see available model documentations (Cambridge Econometrics 2014; Barker and Scrieciu 2010) or go to the website https://www.e3me.com/.

GCAM

The Global Change Assessment Model (GCAM) is a global, multi-regional integrated assessment model. GCAM is an open-source model primarily developed and maintained at the Joint Global Change Research Institute. GCAM was one of the four models chosen to create the representative concentration pathways (RCPs) for the IPCC's AR5. GCAM was also among six models chosen to create the shared socioeconomic pathways (SPPs). The full documentation of GCAM is available at http://www.globalchange.umd.edu/gcam/.

GCAM links economic, energy, land-use, water, and earth systems. Producers maximise their profits while consumers minimise their costs. Market equilibrium is achieved by adjusting the price levels at which demand and supply balance each other out. GCAM is a recursive dynamic model (i.e. no intertemporal optimisation conducted) and the market equilibrium is solved for every 5 years over 2005-2100.

The energy system module of GCAM includes different processes and activities starting from resource extraction, conversion, transmission and delivery and ultimately providing energy services for different end-use sectors. Resources are classified as depletable and renewables. The extraction costs increase as the most cost-effective resources are depleted.. However, this is also subject to technological progress resulting in lower extraction costs for a given resource grade. Energy transformation sectors convert resources into fuels consumed by other transformation sectors, and ultimately into goods and services consumed by end-use sectors. The prices of fuels are calculated endogenously in each time period. The land-use model endogenously calculates the costs of biomass. CCS is available for all fuel types starting in the year 2020. CO_2 storage can also be treated as a finite geographically distributed source, while the model distinguishes between five different geologic storage reservoir types. Each type of reservoir is associated with a cost of storage, depending on the difficulty of access. International trade is modelled for energy commodities, agricultural and forest products, and other goods such as emission permits.

GCAM is the "marker" (representative) model of the SSP4 Inequality Storyline (Calvin et al., 2017). SSPs (Shared Socioeconomic Pathway) are storylines that have been developed by the IAM community to represent a range of future socio-economic developments. The SSP4 (inequality) scenario represents a world characterized by high adaptation challenges and low mitigation challenges.

GEM-E3

General Equilibrium Model for Energy-Economy-Environment interactions (GEM-E3) has been developed as a multinational collaboration project[361]. GEM-E3 is a top-down model used

[361] The model is the result of a collaborative effort by a consortium involving: National Technical University of Athens (NTUA/E3M-Lab) (leading partner), Katholieke Universiteit of Leuven (KUL), University of Manheim and the centre for European Economic Research (ZEW), Ecole Centrale de Paris (ERASME) as the core modelling team. It was partly funded by the Commission of the European Communities, DG Research, 5th Framework programme and by national authorities, and further developments are continuously under way.

regularly to provide analytical support to European Commission. GEM-E3 is a global, multi-regional, multi-sectoral, recursive dynamic CGE model. It covers 38 World regions and 31 economy sectors linked through trade flows. Following a micro-economic approach, it formulates the supply or demand behaviour of the economic agents regarding production, consumption, investment, employment and allocation of their financial assets. Prices are computed by the model as a result of supply and demand interactions in the markets. For a detailed description of the GEM-E3 model we refer to available model documentations (Capros et al. 2013; E3M Lab, n.d.) or the website of the EU Commission (https://ec.europa.eu/jrc/en/gem-e3/model).

IMAGE

Integrated Model to Assess the Global Environment (IMAGE) is a global, multi-regional integrated assessment model developed by the IMAGE team under the authority of PBL Netherlands Environmental Assessment Agency. Its documentation can be found on the PBL website[362]. The framework consists of a set of linked and integrated sub-models that in combination represent elements of the long-term dynamics of global environmental change, simulating consequences of human activity, including aspects such as air pollution, climate change, and change in land-use.

IMAGE is characterized by relatively detailed biophysical processes and a wide range of environmental indicators and covers a broad range of environmental and sustainability issues, while it has less detail on economics and policy instruments than other IAMs. Comprehensive and balanced integration of energy and land systems was initially another pioneering feature of IMAGE. However, other IAMs are evolving in similar direction by focusing on enhancing the representation of their land-use systems and therefore converging in this respect. IMAGE has less detail on economics and policy instruments than other models. The IMAGE modelling framework is considered as a partial equilibrium model as it is not linked to a macroeconomy model. Exogenous economic projections (for example based on the OECD ENV-Growth model) are used as input to determine energy (and water) demand.

The IMage Energy Regional model (TIMER) is a global energy system model that forms a submodule of the IMAGE modelling framework to describe the long-term dynamics of the energy system. TIMER models various processes of energy production to satisfy the energy demand and quantifies the associated GHG emissions and regional air pollutants.

Demand and production of agricultural products are modelled by soft-linking to the agroeconomic model MAGNET or alternatively IMPACT. MAGNET provides information on future agricultural production levels and intensity by region. The regional demands are balanced via trade. . A key purpose of the agroeconomy model is to determine regional production levels and the associated yields and livestock efficiencies, taking into account changes in technology and biophysical conditions. An increase in demand for agricultural production can be met by land expansion (using the regional land supply curves) and/or intensification of land use and increasing yields. For a detail description of IMAGE model we refer to (Stehfest et al., 2014).

The IMAGE model is the marker scenario of the SSP1 (Sustainability) storyline, due to its ability to cover a wide range of sustainability indicators. This storyline is characterized by low challenges both for mitigation and adaptation.

IMACLIM

IMACLIM-R model from the Centre international de recherche sur l'environnement et le développement (CIRED) is a multi-region and multi-sector model covering the global economy.

[362] https://www.pbl.nl/en/image/about-image or https://models.pbl.nl/image/index.php/Welcome_to_IMAGE_3.0_Documentation

For this, is bring together a Computable General Equilibrium (CGE) framework with bottom-up sectoral modules in a hybrid and recursive dynamic set up. [363] Using recursive dynamics, the equilibrium is solved in each year the equilibrium based on a system of non-linear equations. It covers the sectors energy, transport and residential/commercial in physical and economic terms and the sectors industry and agriculture in economic terms.[364] The energy sector is moreover split into five sub-sectors: 'oil extraction', 'gas extraction', 'coal extraction', 'refinery' and 'power generation'. The transport sector is split into three sub-sectors: 'terrestrial transport', 'air transport', 'water transport' while the industry sector features only one sub-sector which is 'energy intensive industry'.[365]

For each region the model represents 14 economic agents: one representative household, one representative firm for each of the 12 sectors per sector respectively and the public administration.[366] A special characteristic of IMACLIM is that it describes growth patterns assuming 'second best' conditions such as market imperfections, incomplete exploitation of production factors and imperfect expectations.

IMACLIM-R is part of the IMACLIM network.[367]

MESSAGE-IAM

MESSAGE-IAM is the global, multi-regional integrated assessment model developed at IIASA, Austria.[368]

Model for Energy Supply Strategy Alternatives and their General Environmental impacts (MESSAGE) is a global system engineering optimisation model dividing the world into 11 regions. The model's main objective is to optimize the energy supply mix over time to satisfy given regional energy demands by minimising the net-present value of total system costs. MESSAGE is rich in terms of modelled energy technology options, from resource extraction, up to conversion and secondary energy level, in particular, electricity and heat generation as well as end use technologies. Finally, MESSAGE also tracks the sources and sinks of GHGs and endogenously evaluates anthropogenic GHG emissions (Fricko et al., 2016).

The energy system model "MESSAGE" is further linked to a macroeconomic model via "soft linking" approach, building a general equilibrium (GE) type IAM "MESSAGE-MACRO" (Messner & Schrattenholzer, 2000). MACRO maximizes the intertemporal utility function of a single representative producer-consumer in each world region. The main variables of the model are the input factors of capital stock, labor, and energy, which together determine the total output of an economy based on a nested production function with constant elasticity of substitution.

Land-use dynamics are modelled with the GLOBIOM (GLobal BIOsphere Management) model, which is a recursive-dynamic partial-equilibrium model (Havlík et al., 2014). GLOBIOM represents the competition between different land-use based activities. It includes a bottom-up representation of the agricultural, forestry and bio-energy sector, which allows for the inclusion of detailed grid-cell information on biophysical constraints and technological costs, as well as a rich set of environmental parameters, incl. comprehensive AFOLU (agriculture, forestry and other land use) GHG emission accounts and irrigation water use. Its spatial resolution allows

[363] See https://www.iamcdocumentation.eu/index.php/Model_scope_and_methods_-_IMACLIM (last accessed Nov 27, 2020)

[364] See https://www.iamcdocumentation.eu/index.php/IMACLIM (last accessed Nov 27, 2020)

[365] See https://www.iamcdocumentation.eu/index.php/IMACLIM (last accessed Nov 27, 2020)

[366] See. https://www.iamcdocumentation.eu/index.php/Macro-economy_-_IMACLIM (last accessed Nov 27, 2020)

[367] http://www.centre-cired.fr/fr/imaclim-network-fr/ (last accessed Nov 27, 2020)

[368] For more details see http://www.iiasa.ac.at/web/home/research/modelsData/MESSAGE/MESSAGE.en.html (last accessed Nov 27, 2020)

representing bilateral trade. For spatially explicit projections of the temporal variations of afforestation, deforestation, forest management, and their related CO_2 emissions, GLOBIOM is further coupled with the G4M (Global FORest Model) model. As outputs, G4M provides estimates of forest area change, carbon uptake and release by forests, and supply of biomass for bioenergy and timber.

Air pollution implications are derived with the GAINS (Greenhouse gas–Air pollution INteractions and Synergies) model. The GAINS model derives cost-effective emission control strategies to meet environmental objectives over a time horizon until 2030. nitrogen oxides (NO_x), ammonia (NH_3), non-methane volatile organic compounds (VOC), and primary emissions of particulate matter (PM), including fine and coarse PM as well as carbonaceous particles (BC, OC). The response of the carbon-cycle and climate to anthropogenic climate drivers is modelled with the MAGICC model. Complete description of the model and mathematical formulations can be found at https://data.ene.iiasa.ac.at/message-globiom/.

The IAM MESSAGE is the marker scenario of the SSP2 (Middle of the Road) storyline, characterized by intermediate challenges both for mitigation an adaptation. This storyline assumes a continuation of current trends in terms of population, GDP and technological developments.

MERGE

Model for Estimating the Regional and Global Effects of Greenhouse Gas Reductions (MERGE) is a global, multi-regional integrated assessment model, disaggregating the world into nine regions. It combines a 'top-down' Ramsey type economic model with a 'bottom-up' engineering optimisation model, and a simple climate model. MERGE may be applied in a "cost-effective" mode, leading to a cost-optimal time path of emissions that satisfies a constraint on concentrations or represented as a temperature target. The model may also be applied in a "cost-benefit" mode, where benefits are described in terms of the damages avoided. For a thorough description of the model and formulations, please see (A. S. Manne & Richels, 2005).

REMIND

Regional Model for Investment and Technological Development (REMIND) is a global, multi-regional integrated assessment model developed at the Potsdam Institute for Climate Impact Research, Germany. For a detail description of model structure and assumptions see (Luderer, Leimbach, Bauer, Kriegler, Baumstark, Giannousakis, et al., 2015)

It represents an intertemporal optimisation tool linking a Ramsey-type economic growth model with a bottom-up energy system optimisation model and a simple climate model. It maximises global welfare subject to equilibrium conditions on different markets and other user-defined restrictions, mainly emission constraints. The macro-economic core of REMIND is a Ramsey-type optimal growth model, maximising inter-temporal welfare based on assuming perfect foresight. The macroeconomic core of REMIND is hard linked to a detailed energy system model. The main advantage of REMIND is a high technological resolution of the energy system with more than 50 conversion technologies and intertemporal trade relations between the 11 world regions. The energy system module considers endogenous technological change. Considered Learning-curves affect the investment costs of wind and solar technologies.

The energy sector demands primary energy carriers (including fossil fuels, nuclear, renewables, etc.) that are converted into final energy carriers; these are then supplied to the macro-economic sector, which in turn uses them in combination with capital and labor to generate GDP. GDP is allocated to investments or final (composite) consumption of goods, after deducting for energy expenditures. Representative agents for each region maximize intertemporal welfare, which is defined as the sum of discounted utilities of private consumption of goods, by using a pure rate of time preference of 3 % per year. Hence, the model finds the optimal investment path while balancing the trade-off between current and future consumption of final goods. Trade is modelled for coal, gas, oil, uranium, and the residual composite good as well as for emission permits.

REMIND uses reduced-form emulators derived from the detailed land-use and agricultural model MAgPIE to represent land-use and agricultural emissions as well as bioenergy supply and other land-based mitigation options. REMIND can also be run in fully coupled mode with the MAgPIE model. REMIND is further linked to a climate module.

POLES

The Prospective Outlook on Long-term Energy System (**POLES**) is a bottom-up partial-equilibrium model of the world energy system. It was initially developed in the 1990s at the University of Grenoble (France) and later on by the Joint Research Centre (JRC) of the European Commission.

The model benefits from a global coverage while keeping regional detail. It provides comprehensive energy balances for 66 countries and regions, among them the members of the OECD and key developing countries. It covers an annual time step with a projection horizon until 2050. The dynamics of the model are based on a recursive simulation process of energy demand and supply. The POLES model covers the entire energy sector, from the primary energy supply sector to detailed demand modules (industry, transport, residential and services,). The latter is an important feature of the POLES model, as it contains modules for a diverse set of energy-intensive sectors such as iron and steel production, and different transport modes.

The JRC has co-developed the model and recently issued the **POLES-JRC** version. A detailed description of the JRC model can be found here: https://ec.europa.eu/jrc/en/poles . POLES-JRC is the European Commission's in-house tool for analyses on global and long-term of climate policies and development of energy markets. Similar to the original POLES model, POLES-JRC also includes a comprehensive description of the energy system while demand and supply are linked through prices and it includes detailed representation of end-use sectors, power generation and other transformation sectors as well as primary supply. For very long-term climate mitigation assessments the model can be run to 2100. For a thorough description of the model, please see (Keramidas et al., 2017b).

WITCH

The World Induced Technical Change Hybrid (WITCH) is a global, multi-regional integrated assessment model, disaggregating the world into 13 regions (www.witchmodel.org).

The economy is modelled through an intertemporal Ramsey-type neoclassical optimal growth model. For each of the model region, a forward-looking central planner maximises intertemporal welfare for the region defined as the regional present value of log per capita consumption, choosing the optimal dynamic path for investments in the main economic variables.[369] . Compared to other IAMs (e.g. GCAM, MESSAGE-IAM, REMIND), WITCH describes the macro-economy component in greater detail, while those models are more detailed in their description of energy technologies compared to WITCH (Bosetti et al. 2015).

A key distinguishing feature of WITCH is the endogenous representation of R&D diffusion and innovation processes. On the one hand, dedicated R&D investments enhance energy efficiency,

[369] https://www.iamcdocumentation.eu/index.php/Model_Documentation_-_WITCH

leading to higher productivity of energy inputs in generating energy services in the energy demand side. On the other, a learning by doing effect in the supply side reduces the cost of new energy technologies (e.g. renewables). Early retirement of power generating technologies is allowed (e.g. phasing out coal power plants earlier than the remaining economic lifetime).

WITCH's top–down framework leads to a coherent, fully inter-temporal allocation of investments that have an impact on the level of mitigation including, investments in energy technologies and R&D as well as expenditures on fossil fuels.

The top-down, intertemporal optimal growth model of economy is hard linked to a bottom-up energy system module. The energy system module constitutes the power sector, transportation sector, and an aggregated non-electric (industry and residential) sector.

In WITCH, the GDP is a function of different input factors including labour, capital and energy use, by using a constant elasticity of substitution production function. This simply means that it would be possible to substitute a factor of production with another (e.g. capital with labour or coal with renewables), but at increasing costs. Technological progress in the energy sector is endogenous, which allows to account for the interplay between different timing and stringency of climate policies and induced technical change. Based on its hybrid nature, the endogenous technological change is thus accounted for both in bottom-up and top-down dimensions.

Mitigation options related to land use are represented through a soft link with GLOBIOM, a land use and forestry model (Bosetti et al. 2015). Emissions are fed into a climate module (MAGICC6) to compute the climate outcome. Climate change affects economic output through a damage function, which also accounts for investments into adaptation, allowing to assess the full dynamics of mitigation and adaptation (Bosetti et al. 2015).

For a thorough description of the model and mathematical formulations, please see (Bosetti et al. 2007; Bosetti et al. 2008; Bosetti et al. 2015).

PRIMES

Price-Induced Market Equilibrium System (PRIMES) model has been developed by the Energy-Economy- Environment Modelling Laboratory at the National Technical University of Athens in as part of a series of research programmes co-financed by the European Commission. A more detailed description of the model can be found under https://ec.europa.eu/jrc/en/poles, a summary of the information is given below.

PRIMES is an established model which has been widely used in analyses of medium- and long-term restructuring of the European energy system, assessing climate change mitigation, renewable energy development, and energy efficiency, as well as for impact assessments of a number of energy and environmental policies including on the community level. The distinctive feature of the PRIMES model is the combination of behavioural modelling based on a micro-economic foundation with engineering and system aspects, covering all energy sectors and markets in a high level of detail.[370] The PRIMES model uses prices for balancing demand and supply simultaneously in several energy and emissions' markets. Technology learning and economies of scale are additionally included and are dealt with endogenously. In this respect, PRIMES is more aggregated than engineering models, but far more disaggregated than

[370] The model's modular system design aims at representing agents' behaviors and their interactions in multiple markets. The agents' behaviours are modelled at the sectoral level based on a microeconomic foundation. Each demand module formulates a representative agent maximising benefits from energy demand and non-energy inputs (commodities, production factors) subject to prices, budget and other constraints including constraints on the availability of fuels or technology. Each supply module on the other hand represents stylised businesses aiming at minimising costs (or maximising profits in model variants with market competition) to meet demand and comply with constraints to capacities, fuel availability, environmental constraints, system reliability, among others. The sub-models are linked using an algorithm which determines equilibrium prices and volumes in multiple markets under the constraints.

econometric models. The PRIMES model assumes perfect foresight over a short-term horizon for demand sectors and perfect foresight over a long-term horizon for supply sectors. The sub-models are solved over the entire time horizon in each cycle of interaction between demand and supply, yielding a dynamic market equilibrium. The PRIMES model particularly differs from optimisation energy models we discussed earlier through this subchapter, for example MARKAL, or TIMES. Such models formulate a single mathematical programming problem, while they do not explicitly account for energy price formation and have no or a simplified aggregated representation of energy demand. In contrast, the PRIMES model formulates separate objective functions per energy agent, it simulates the formation of energy prices explicitly and represents energy demand, as well as energy supply also in detail. On the other hand, PRIMES is a partial equilibrium model as opposed to general equilibrium models, such as GEM-E3. PRIMES cannot perform energy-economy equilibrium analysis in a closed loop, unless it is coupled with a macroeconomic model such as GEM-E3. According to these specific distinguishing features of the PRIMES model, it is neither completely consistent with bottom-up optimisation models of energy system models such as TIMES, MARKAL, POLES nor with top-down macroeconomy models elaborated earlier. PRIMES may also be classified as a hybrid model according to the fact that it captures technology and engineering detail together with micro and macro interactions and dynamics according to (E3MLab/ICCS, 2014). Additionally, there exist hybrid modelling frameworks developed by coupling the PRIMES energy system model with economy models as well as emissions and environmental assessment models. For instance, the PRIMES- GEM-E3 – GAINS hybrid framework links the PRIMES model with the CGE model "GEM-E3" and IIASA's GAINS model (for non-CO_2 gases and air quality) to build a hybrid model to perform energy-economy-environment policy analysis within a closed-loop. When PRIMES is linked with the macroeconomic model GEM-E3, the coverage of projection data for the purposes of cost-benefit assessment is completer and more comprehensive. Similarly, when linked to the GAINS model, it provides a larger coverage of cost-benefit projections with respect to air pollution and related health effects. For further description of the PRIMES model and mathematical formulations see (E3MLab/ICCS, 2014).

WIAGEM

World Integrated Assessment General Equilibrium Model (WIAGEM) is an integrated assessment model that has been developed at the German Institute for Economic Research (DIW Berlin). The model comprises 25 world regions aggregated into 11 trading regions, with 14 sectors respectively. WIAGEM integrates an economy model based on a dynamic intertemporal general equilibrium approach combined with an energy market model and a climatic submodel covering a 50 years time horizon. As its particular characteristic, the economy is represented by an intertemporal computable general equilibrium (CGE) and multi-regional trade model.[371]

WIAGEM has however not been actively used in recent years and it has also not been part of multi model studies to our knowledge.

D.1.1 Interlinkages between authors – Co-authorship

Taking one perspective on modelling communities, we analyse the ties/links between authors active in the field of climate change mitigation and cost assessment based on co-authorship relations between authors. Using the social network analysis tool VOSviewer[372] which allows to

[371] See Kemfert (2002) An Integrated Assessment Model of Economy-Energy-Climate – The Model Wiagem, in: Integrated Assessment2002, Vol. 3, No. 4, pp. 281–298.

[372] Software can be downloaded for free under http://www.vosviewer.com/ or used as online version.

visualize bibliometric networks, we identify which authors in our literature database compiled for this report are key nodes in the overall network and which have frequently cooperated in the form of common publications (co-authorships). For this, we exploited the full literature database that was compiled for this study.[373] However, while we conducted an extensive literature research on mitigation cost assessment and related literature, we do not claim to have an exhaustive coverage of all literature in this very broad and active field. Moreover, as the main interest of this report lies on literature with i) a focus on Europe, ii) long-term transformation pathways as well as iii) more recent literature. Thus, literature on other world regions, studies focusing on short- to medium term mitigation or older literature is likely underrepresented in our literature database. Yet, the analysis serves well to identify:

- key authors who are particularly active in publishing in the field
- (sub-)networks of authors that have frequently cooperated by coauthoring publications
- key authors who are particularly active in linking with other authors in the field constituting important nodes of the network and sub-networks
- clusters of author groups and
- interlinkages between these clusters.

To also identify linkages between authors active on the damage costs side and the mitigation cost side, the network analysis is based on the whole literature used for all chapters of this report.[374] The size of the node for each author reflects the number of publications of this author in the database, while the strength of the linking line reflects the number of co-authorships between authors.[375]

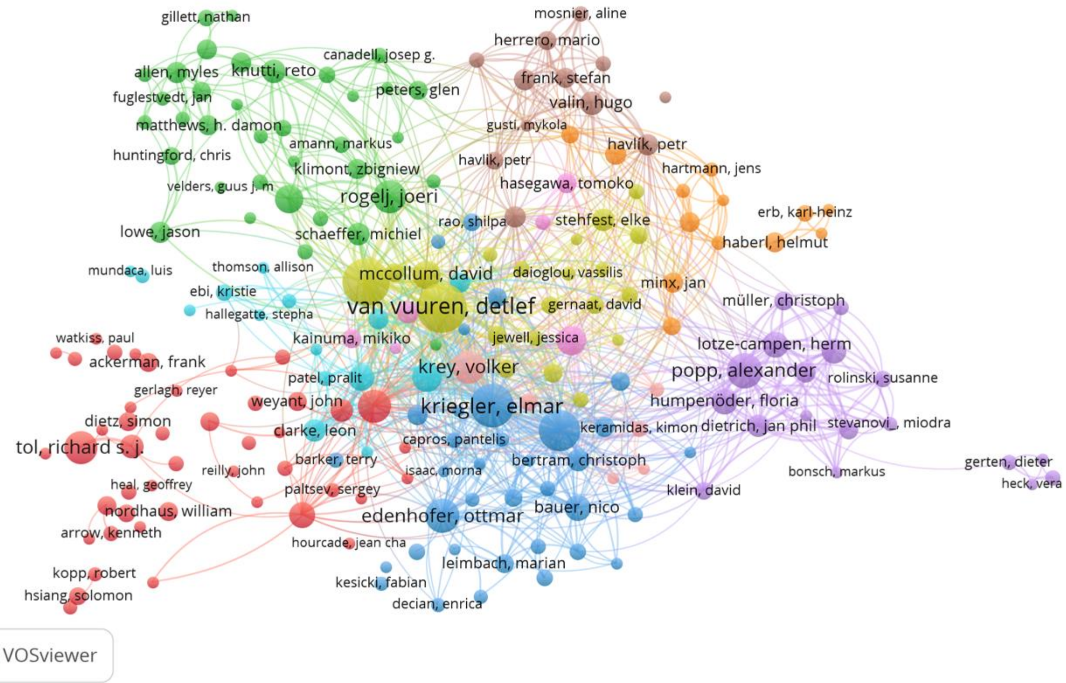
Figure 110 shows the network between authors in our literature database identifying various key authors that are particularly active in the field as well as clusters of author groups

[373] To improve readability of the figures and exclude authors with lower relevance in this particular field, we chose a minimum number of publications included in our literature database per author (see appendix for a comparison between displaying 3 or 4 as minimum number of publications to be included in figure). Moreover, we excluded reports with more than 25 authors and we excluded reports authored by institutions (such as IEA, UNEP, etc) without clear identification of authors.

[374] See remarks in footnote above on which literature has been excluded for graphing to improve readability of the figures. Moreoverm studies included in the report after August 2019 have not been taken into account.

[375] There are two options to account for co-authorship linkages, 1) *Full counting*, i.e. each co-authorship is counted as one link independent of the number of co-authors for the same publication and 2) *Fractional counting*, i.e. weighing the co-authorship link by the number of authors for the same publication giving a lower weight to publications with many co-authors (For example, if an author has 10 co-authors for the same publication, the link to each co-author is weighted 1/10). As studies based on modelling often involve a large number of co-authors while the intensity of cooperation and exchange between authors can still be strong, we focus on showing the network between authors using full counting.

Figure 110: Network of authors and clusters based on co-authorship analysis



Full Counting of co-authorship links. Min. number of publications in database per author is 4.

Source: Based on Zotero Literature database compiled for this report, using the VOSviewer tool.

D.1.2 Cooperation between models – Joint participation in multi-model studies

Table 46: Overview on participation of models in multi-model studies

Model Inter-comparisons / multi-model Studies Models Included	AME 2012	LIMITS 2014	AMPERE 2014	RoSE 2014	EMP27 2014	ADVANCE 2018	CD LINKS 2018	SSPx 2018	Assessment of EU long-term vision 2018
AIM								x	
AIM/CGE	x					x			
AIM/CGE 2.1							x		
AIM/ENDUSE	x				x				
BET					x				
BLUES						x			
China MARKAL/TIMES				x					
DNE21+	x		x		x	x			
EC-IAM					x				
ENV-Linkages					x				

Model Inter-comparisons / multi-model Studies Models Included	AME 2012	LIMITS 2014	AMPERE 2014	RoSE 2014	EMP27 2014	ADVANCE 2018	CD LINKS 2018	SSPx 2018	Assessment of EU long-term vision 2018
EPPA	x								
E3ME									x
FARM					x				
GCAM	x	x	x	x	x	x		x	
GCAM-IIM	x				x				
GCAM USA CD LINKS							x		
GEM-E3	x		x			x			
GRAPE	x				x				
GTEM	x								
IMACLIM			x		x	x			
IMAGE	x	x	x		x	x		x	
IMAGE 3.01							x		
IPAC				x					
IPETS	x					x			
JRC-GEM-E3									x
KEI-LINKAGE	x								
MARIA-23	x								
MERGE	x				x				
MERGE-ETL			x						
MESSAGE	x	x	x		x	x			
MESSAGE-GLOBIOM								x	
MESSAGE-GLOBIOM 1.0							x		
NEPAL MARKAL	x								
NMESIS			x						
PECE	x								
Phoenix	x				x				
POLES			x		x	x	x		
POLES-ITS	x								
PRIMES-GAINS-GLOBIOM									x

Model Inter-comparisons / multi-model Studies Models Included	AME 2012	LIMITS 2014	AMPERE 2014	RoSE 2014	EMP27 2014	ADVANCE 2018	CD LINKS 2018	SSPx 2018	Assessment of EU long-term vision 2018
QUEST									x
REMIND	x	x	X	x	x	x			
REMIND MAgPIE								x	
REMIND MAgPIE 1.7-3.0							x		
TIAM-ECN		x							
TIAM-UCL						x			
TIAM-WORLD	x				x				
TIMES-VTT	x								
WITCH	x	x	x	x	x			x	
WITCH-GLOBIOM 4.4							x		
WorldScan2			x						

Source: own illustration, Climate Analytics based on the descriptions from selected model intercomparisons and information provided in the IPCC AR5 WGIII report (Edenhofer et al., 2014)

Table 47: Overview on multi-model studies

(Short) title of multi-model study (year*)	Focal question(s) / main driver(s) analysed [H: Areas of Harmonisation]	Models included (model type)	Includes estimates for EU/Europe	Main reference(s)
Pre AR5:				
ADAM (2009) (Adaptation and Mitigation Strategies—Supporting European Climate Policy)	• Supporting the EU in developing a post-2012 climate policy (post Kyoto 2012), in defining a European mitigation strategy • [H: Technology availability, Mitigation policy]		Yes, Europe focus	• Edenhofer O., B. Knopf, M. Leimbach, and N. Bauer (2010). ADAM's Modelling Comparison Project-Intentions and Prospects. The Energy Journal 31, 7-10.
RECIPE (2009) (Report on Energy and Climate Policy in Europe)	• [H: Mitigation policy]	ReMIND-R, WITCH, IMACLIM-R	Yes, Europe focus	• (Luderer et al., 2012)

(Short) title of multi-model study (year*)	Focal question(s) / main driver(s) analysed [H: Areas of Harmonisation]	Models included (model type)	Includes estimates for EU/Europe	Main reference(s)
AME (2012) (Asian Modeling Exercise)	• Better articulate the role of Asia in mitigating climate change, focusing on results for Asian regions • [H: Mitigation policy]	23 energy-economic and integrated assessment models: AIM CGE, AIM ENDUSE, DNE21, EPPA, GCAM, GCAM-IIM, GEM-E3, GRAPE, GTEM, IMAGE, IPETS, KEI-LINKAGE, MARIA-23, MERGE, MESSAGE, NEPAL MARKAL, PECE, PHOENIX, POLES-ITS, REMIND, TIAM-WORLD, TIMES-VTT, WITCH	Yes	• (Calvin et al., 2012)
RoSE (2013) (Roadmaps towards Sustainable Energy futures)	• Fossil fuel resources • Socioeconomic projections • [H: Mitigation policy; GDP growth; population growth, fossil fuel availability]	5 Models: GCAM, IPAC, REMIND, WITCH, China MARKAL/TIMES	Yes[376]	• (Luderer et al., 2016) • (Bauer et al., 2016)
LIMITS (2014) (Low Climate Impact Scenarios and the Implications of required tight emissions control strategies)	• Particular focus on (global and regional) mitigation costs and regional distributional effects (burden sharing) • Policy delay • EU focus region • [H: Mitigation policy]	6 Models: GCAM, IMAGE, MESSAGE, REMIND, TIAM-ECN, WITCH	Yes, EU focus region	• (Kriegler et al., 2013) • (Tavoni et al., 2013) • (Jewell et al., 2016) • (Van Der Zwaan et al., 2013) • (Aboumahboub et al., 2014)
AMPERE (2014) (Assessment of Climate Change Mitigation Pathways and Evaluation of the Robustness of Mitigation Cost Estimates)	• mitigation policy • Technology availability (e.g. impacts of pathways without CCS or nuclear) • Global mitigation costs • Model diagnostics • Policy delay • WP5: decarbonisation scenarios within Europe • [H: Technology availability; mitigation	12 Models: DNE21+, GCAM, GEM-E3, IMACLIM, IMAGE, MERGE-ETL, MESSAGE, NMESIS, POLES, REMIND, WITCH, WorldScan2	Yes (especially WP5)	• (Riahi et al., 2015) • (Kriegler, Riahi, et al., 2015) • (Bertram et al., 2015)

[376] Country coverage of the EUR region vary across models.

(Short) title of multi-model study (year*)	Focal question(s) / main driver(s) analysed [H: Areas of Harmonisation]	Models included (model type)	Includes estimates for EU/Europe	Main reference(s)
	policy; GDP; population]			
EMF -27 (2014) (Energy Modelling Forum 27)	• Technology availability • [H: Technology availability; mitigation policy]	18 Models: AIM/End Use, BET, DNE21+, EC-IAM, ENV-Linkages, FARM, GCAM, GCAM-IIM, GRAPE, IMACLIM, IMAGE, MERGE, MESSAGE, Phoenix, POLES, REMIND, TIAM-World, WITCH	Partly	Special Issue in *Climate Change*, Volume 123, Issue 3-4, April 2014
Post AR5:				
CD-LINKS (2018) (Linking **C**limate and **D**evelopment Policies – **L**everaging **I**nternational **N**etworks and **K**nowledge **S**haring)	• Policy Focus: Exploring interactions between climate and sustainable development policies with the aim to identify robust integral policy packages to achieve all objectives	7 Models: AIM/CGE 2.1, GCAM USA CD-LINKS, IMAGE 3.01, MESSAGEIX GLOBIOM 1.0, POLES, REMIND MAgPIE 1.7-3.0, WITCH GLOBIOM 4.4	No, only OECD-90 (incl. EU)	• CD-LINKS webpage[377] • (McCollum et al., 2018)
SSPx (2018)	• Development of new community scenarios based on the full SSP framework limiting end-of-century radiative forcing to 1.9 W m^{-2}	6 Models: IMAGE, MESSAGE-GLOBIOM, REMIND-MAgPIE, WITCH, AIM, GCAM		• (Riahi et al., 2017) • (Rogelj, Popp, et al., 2018)
ADVANCE (2018) (Advanced Model Development and Validaton for the Improved Analysis of the Costs and Impacts of Mitigation Policy)	• NDC focus • Enhancing representation of energy systems • Diagnostics	12 Models: AIM/CGE, BLUES, DNE21+, GEM-E3, IMACLIM, REMIND, MESSAGE, GCAM, IMAGE, POLES, TIAM-UCL, IPETS	Partly	• (Luderer Gunnar et al., 2016) • (Vrontisi et al., 2018) • (Luderer et al., 2018)

* year in which project ended or main publication has been published. For Model Intercomparison Projects, the individual publications related to the larger project can have different publication years.

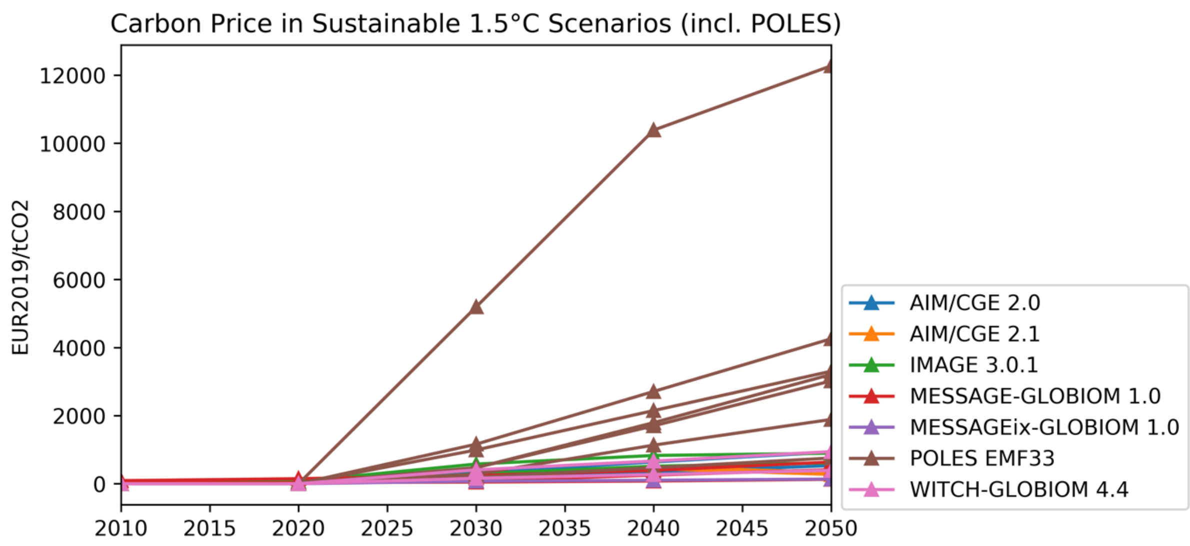
Source: Adjusted from Table A.II.15 of the Metrics and Methodology Section of the IPCC's AR5 WGIII report (Edenhofer et al., 2014)

[377] https://www.cd-links.org/?page_id=620

D.1.3 Special Report 1.5 database

Figure 111: Carbon price developments over time for filtered pathways from the IPCC SR1.5 (including POLES)

Filtering 'sustainable' pathways



Definition of 'sustainable': The IPCC, based on Fuss et al. (2018), finds limits for a sustainable use of both Carbon Dioxide Removal (CDR) options globally by 2050 to be below 5GtCO_2 p.a. for BECCS and below 3.6GtCO_2 p.a. for sequestration through Afforestation and Reforestation while noting uncertainty in the assessment of sustainable use and economic and technical potential in the latter half of the century. Pathways from the SR1.5 database have been filter based on these criteria. To improve readability, the outlier POLES has been included here. Carbon prices in USD2010 have been converted to EUR 2019 using the same conversion factors and sources for these as in Figure 54 (UNCTADSTAT 2010) and (Statistisches Bundesamt (Destatis), 2020)).

Source: own illustration, Climate Analytics based on SR1.5 database (Huppmann et al., 2019).

D.1.4 ADVANCE model inter-comparison project and database

20.5.1.1 Brief introduction to the ADVANCE project

The ADVANCE project[378] is a model intercomparison project that officially ran from 2013 to end of 2016. Most publications have been published around 2018 and 2019, and the related database[379] went online in mid 2019.

As discussed in section 5.3, Integrated Assessment Models (IAMs) play an important role in the climate policy arena and have been increasingly applied to investigate consistent transformation pathways in line with long-term temperature goals. This includes questions related to various technological and socio-economic developments for energy system, land-use and climate. With a growing use and complexity of these models, the demand for improved representation of 'real world conditions' and validation of model behaviour has grown significantly over recent years.

[378] More information on ADVANCE and related publications as well as involved institutes can be found on the project website http://www.fp7-advance.eu/ .

[379] The database can be accessed as a guest under the following link https://db1.ene.iiasa.ac.at/ADVANCEDB/dsd?Action=htmlpage&page=welcome

The ADVANCE project aimed at contributing to improved modelling and model transparency, model validation, and data handling (Luderer et al. 2016):

- Methodological developments under ADVANCE have contributed to improving the representation of the energy-economy-climate system.
- A systematic model documentation of all energy-economy and integrated assessment models participating in the project has been developed.

Improving IAMs would also lead to more robust and transparent estimates regarding the climate change mitigation costs, compared to earlier estimates (for example from the LIMITS and AMPERE projects). However, it should be noted that delivering mitigation cost estimates has not been a key focus of the ADVANCE project, although this information can be derived from the ADVANCE project database from a variety of models.

In total, thirteen energy-economy and integrated assessment models have contributed to the ADVANCE project: IAMs with integrated energy system and General Equilibrium-type growth models including REMIND, MESSAGE-MACRO, and WITCH, as well as CGE-based models including IMACLIM, GEM-E3-ICCS, AIM/CGE, and iPETS and Partial-Equilibrium-type energy system models including IMAGE-TIMER, POLES, TIAM-UCL, REMix, DNE21+, and GCAM. However, in the ADVANCE database only a subset of nine of these models have provided their results and cost estimates. The ADVANCE database is introduced in more detail below.

20.5.1.2 ADVANCE database: Models and Scenarios

The ADVANCE database, which had recently been made publicly available[380], compiles the results of nine models that participated in the ADVANCE project for a set of (harmonized) scenarios (see Figure 112). Note that not all models provide results for all scenarios.

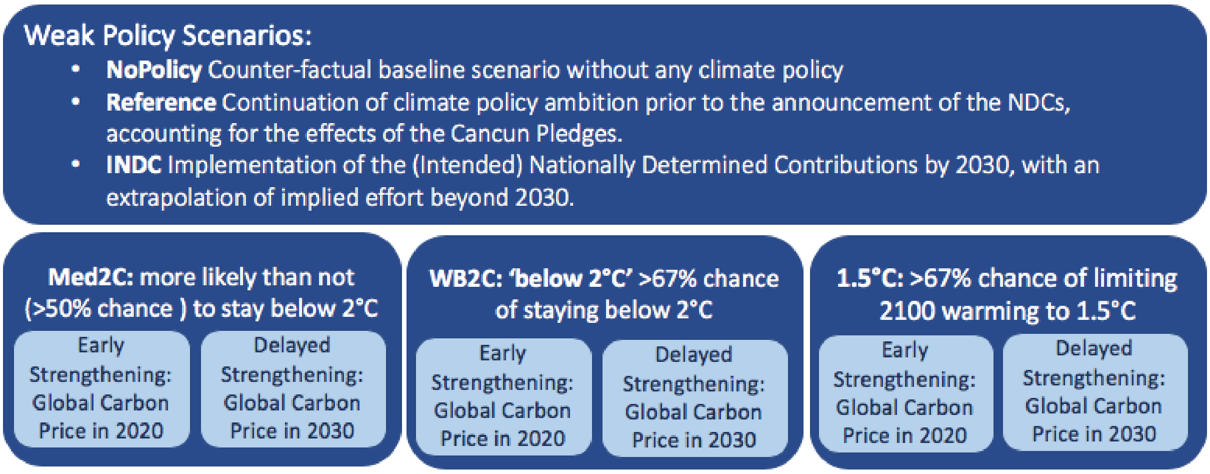
Models in ADVANCE database (model version in brackets):

- AIM/CGE (V.2)
- GCAM (4.2 ADVANCE WP6)
- GEM-E3 (V2)
- IMACLIM (V1.1)
- IMAGE (3.0)
- MESSAGE-GLOBIOM (1.0)
- POLES (ADVANCE)
- REMIND (V1.7)
- WITCH (2016)

[380] The database can be accessed as a guest under the following link https://db1.ene.iiasa.ac.at/ADVANCEDB/dsd?Action=htmlpage&page=welcome

One main aim of the ADVANCE project was to improve transparency and model documentation. A detailed description of the model features and assumptions has therefore been compiled in the project model documentation (model WIKI)[381].

Figure 112: Overview on scenarios in the ADVANCE database



Source: own illustration, Climate Analytics based on information given in the ADVANCE database description https://db1.ene.iiasa.ac.at/ADVANCEDB/dsd?Action=htmlpage&page=welcome

D.1.5 Mitigation cost estimates in the ADVANCE database

As mentioned in Section 17.4.2, not all models report all types of mitigation cost metrics. Table 48 provides an overview on which cost metrics are reported by which model in the ADVANCE database.

Table 48: Overview on mitigation cost metrics reported in ADVANCE database

	Table header	AIM/CGE V.2	GCAM4.2_ADVANCEWP6	GEM-E3_V2	IMACLIM V1.1	IMAGE 3.0	MESSAGE-GLOBIOM_1.0	POLES ADVANCE	REMIND V1.7	WITCH 2016
Reported Policy Costs in ADVANCE database	GDP loss (PPP or MER)	✔	-	-	-	-	✔	-	✔	✔
	Consumption loss	✔	-	-	-	-	✔	-	✔	✔
	Area under MACC	-	-	-	-	✔	-	✔	-	-
	Additional total energy system costs	✔	-	-	-	-	-	-	-	✔
Other metri cs in ADVA	Investment costs (Energy supply)	✔	-	-	✔	✔	✔	✔	✔	✔

[381] https://www.iamcdocumentation.eu/index.php/IAMC_wiki

	Table header	AIM/CGE V.2	GCAM4.2_ADV ANCEWP6	GEM-E3_V2	IMACLIM V1.1	IMAGE 3.0	MESSAGE-GLOBIOM_1.0	POLES ADVANCE	REMIND V1.7	WITCH 2016
	Carbon Price	✔	✔	✔	✔	✔	✔	✔	✔	✔

Source: ADVANCE database.

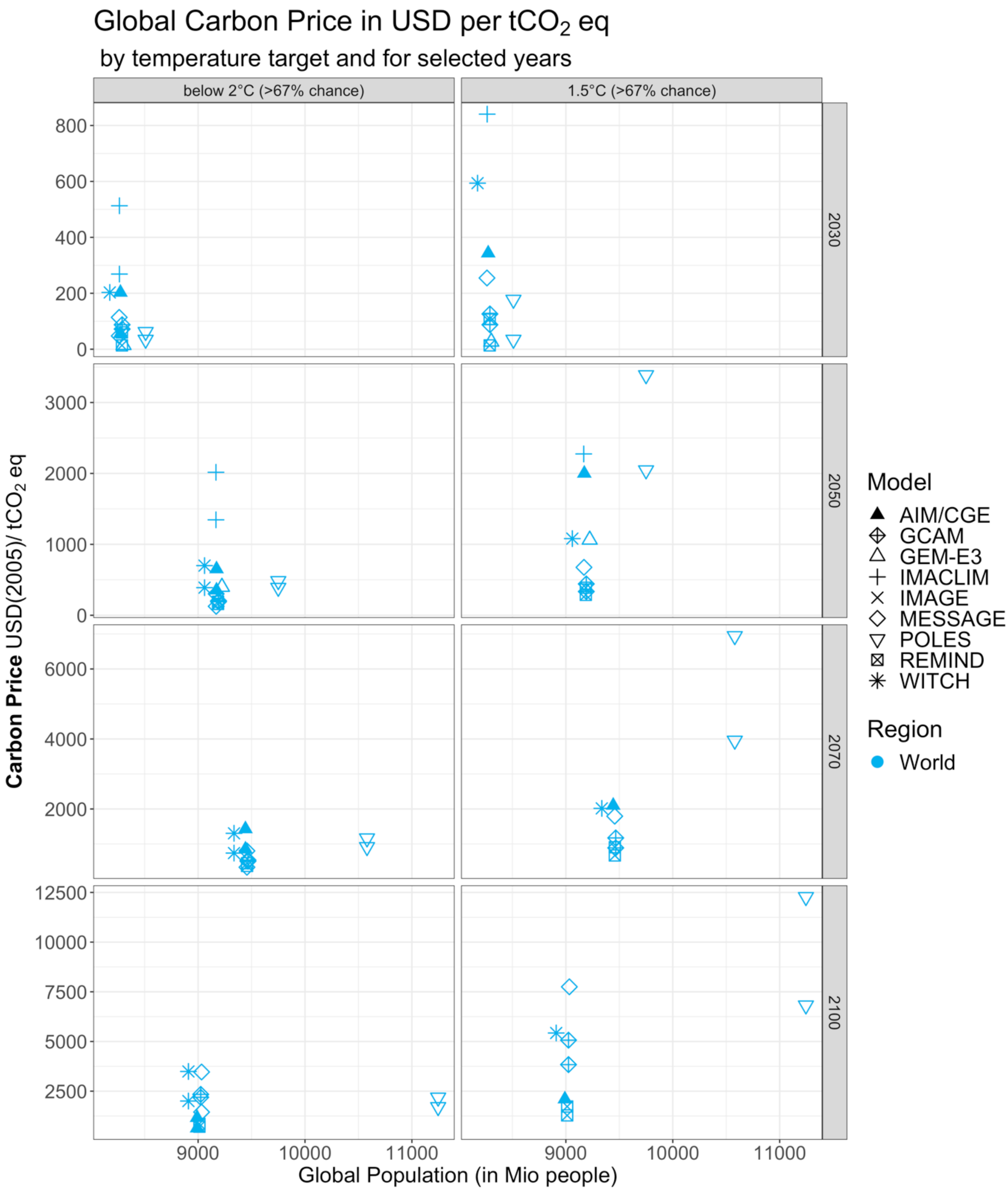
For the analysis of mitigation cost rates, we are mainly interested in the costs per tCO_2. While the carbon price already yields a cost in USD_{2005}/tCO_2 (for marginal costs), the other cost metrics in the ADVANCE database provide values for the total costs reported in USD_{2005}. To obtain cost rates in term of USD_{2005}/tCO_2, we convert these into average unit costs by diving the total mitigation costs compared to the respective baseline by the total amount of avoided emissions compared to the same baseline for each period (see Figure 113).

To calculate absolute (total) changes in GDP and in consumption in USD, we use data on the GDP and consumption trajectories provided in the ADVANCE database for the respective stabilization scenarios and compare it with the available baselines (NoPolicy and Reference Scenario) for each time period, respectively.

To calculate average changes in GDP or consumption unit of avoided emissions (in USD/tCO2e), we first calculate the total GHG emissions in CO2 equivalents for each scenario using Global Warming Potentials from the IPCC's Fifth Assessment Report. We then divide the total absolute change in GDP or consumption the we calculated in the step above by the total amount of avoided GHG emissions (in CO2e) for the respective baseline. This yields average 'unit' mitigation cost estimates measured in USD_{2005}/tCO_2e for each period for the available baseline scenarios, respectively.

For the mitigation cost metrics Area under MAC curve and Additional Total Energy System Costs, we need to rely on reported 'Policy Costs' provided in the ADVANCE database, referring to total costs in USD_{2005}. As above, we divide the total costs by the calculated total avoided GHG emissions (for the scenario that we identify as most likely underlying baseline scenario or based on feedback from the modelers) to obtain average 'unit' mitigation cost estimates measured in USD_{2005}/tCO_2e for each period for the assumed baseline scenario, respectively (see Figure 114).

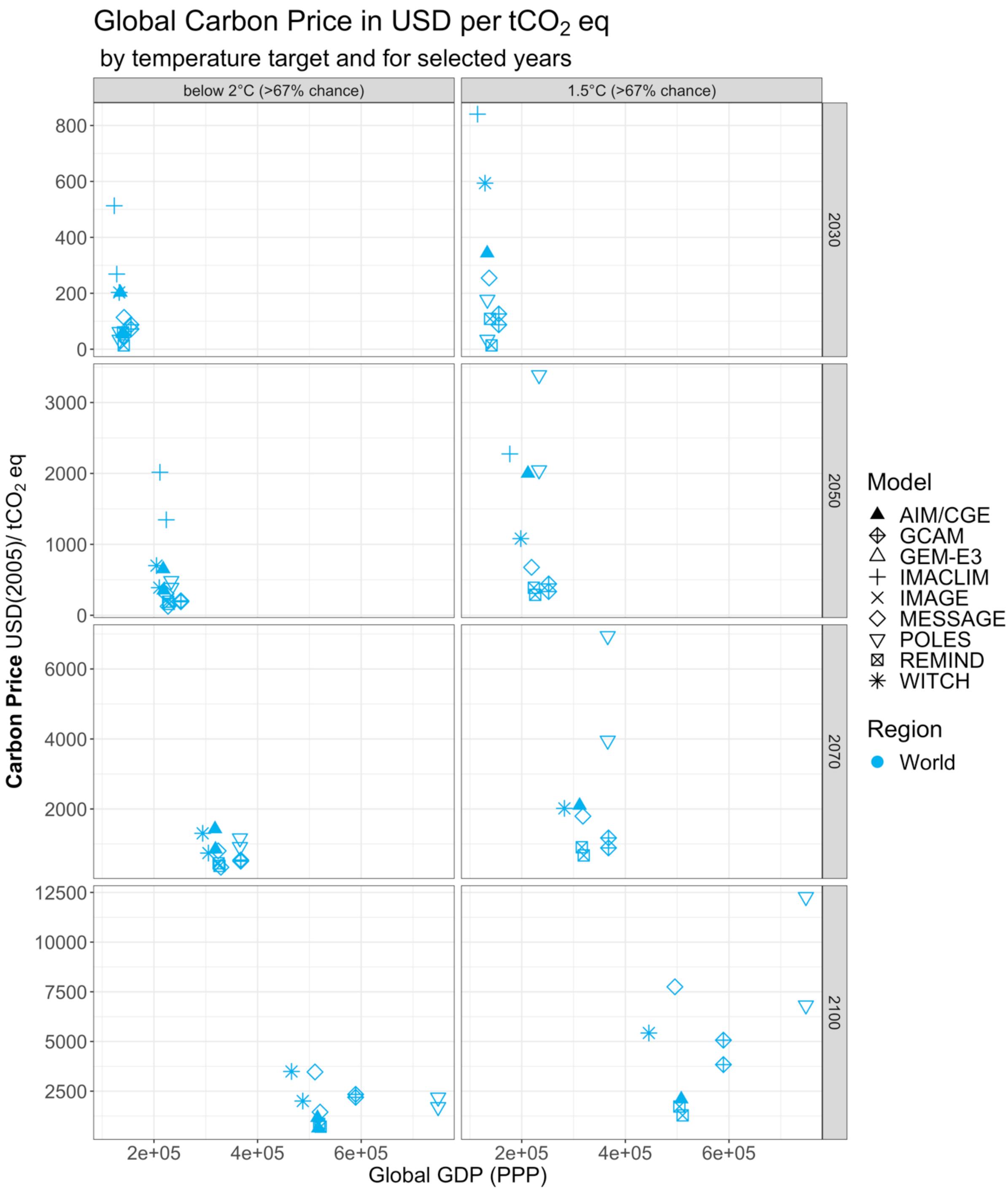
Figure 113: Carbon Price by population (ADVANCE)



Note differences in the y-scales to improve readability. MESSAGE=MESSAGE-GLOBIOM. Note that IMAGE assumes a ceiling value for the carbon price of 4000 USD/tC (1090.91 USD/tCO_2). Note that IMACLIM and GEM-E3 only report results until 2050. Note a potential selection bias for 1.5°C scenario results due to potential infeasibility issues to produce results for very ambitious scenarios.

Source: own illustration, Climate Analytics based on ADVANCE database.

Figure 114: Carbon Price by Global GDP (ADVANCE)



Note differences in the y-scales to improve readability. MESSAGE=MESSAGE-GLOBIOM. Note that IMAGE assumes a ceiling value for the carbon price of 4000 USD/tC (1090.91 USD/tCO_2). Note that IMACLIM and GEM-E3 only report results until 2050. Note a potential selection bias for 1.5°C scenario results due to potential infeasibility issues to produce results for very ambitious scenarios.

Source: own illustration, Climate Analytics based on ADVANCE database.

E Literature

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