HEC MONTRÉAL

Modeling Direct Air Capture in an Integrated Assessment Model

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List of acronyms

BECCS Bioenergy with carbon capture and storage

CCS Carbon capture and storage/sequestration

CDR Carbon dioxide removal

DAC Direct air capture

DICE The Dynamic Integrated Climate-Economy model

EE Energy efficiency

GHG Greenhouse gases

GDP Gross domestic product

GtCO$_2$ Gt (10^9 tons) of CO_2

IAM Integrated assessment model

IEA International Energy Agency

IMF International Monetary Fund

LHS/RHS Left-hand/right-hand side of an equation

MAPE Mean absolute percent error

MERGE A Model for Evaluating the Regional and Global Effects of GHG Reduction Policies

NETs Negative emissions technologies

TFP Total factor productivity

TPES Total primary energy supply

Introduction

The accumulation of greenhouse gases (GHG) in the atmosphere threatens the Earth's global climate balance. To address these threats, three main policy strategies exist:

1. Mitigation: reduction in GHG emissions, the cause of climate change;

2. Adaptation: measures taken to limit the impact of climate change on the society at a given temperature level (e.g. building of sea walls, introducing new crops, etc.);

3. Geoengineering: deliberate altering of the climate system in order to decrease global temperatures. Geoengineering, in its turn, can be further grouped into:

    a) Carbon dioxide removal (CDR) from the atmosphere;

    b) Solar radiation management to reduce incoming solar radiation, for example, injection of sulfur in the stratosphere (Bahn et al., 2015; Belaia, 2019; Barrett et al., 2014).

CDR includes a number of technologies that could allow net removal of CO_2, the main GHG, from the atmosphere, for example, afforestation and reforestation, bioenergy with carbon capture and storage (BECCS), soil carbon sequestration, and direct air capture (DAC), to name a few. While biological CDR methods have been extensively studied, little research has been done so far on abiotic CDR, in particular, on DAC.

DAC technologies capture carbon dioxide directly from the atmosphere. This CO_2 can further be used to produce synthetic fuels (Carbon Engineering, 2019), in enhanced oil recovery or stored in geological formations. When captured CO_2 is stored in geological formations, DAC can generate negative emissions, offsetting to some extent CO_2 emissions produced by economic activity. Such a technology might prove necessary in a situation when despite all international efforts, carbon dioxide emissions keep growing from year to year, thus making drastic climate changes more and more probable.

The objective of this project is to model DAC and its interplay with other climate change strategies - adaptation and mitigation - on the macro level over the long-run horizon. In addition to DAC, we also model carbon capture and sequestration (CCS) - a technology that allows capturing CO_2 right at the place of origin (e.g., at a pipe of a power plant). In both cases, we consider a simplistic scenario when CO_2 is captured and then stored in underground reservoirs and do not model other possible uses of the captured CO_2.

Figure 0.1: How DAC facilities might look like (an image by Carbon Engineering)

To study interactions of various climate policies, we use a computer-based integrated assessment model (IAM). IAMs use linear and non-linear mathematical equations to describe, in an aggregate manner, social-economic, energy, geophysical, and environmental elements and study interactions between them. By combining knowledge from several disciplines in a single framework, IAMs allow understanding how changes in one sphere might impact other spheres. With relation to the climate change, such models often operate with a long-term foresight horizon (looking 100-200 and more years ahead). They are mostly used to understand the implications of alternative policy decisions and model various “what-if” scenarios (CarbonBrief, 2018).

To model climate change and its impacts on the society, multiple IAMs exist, ranging from simpler ones, such as DICE, FUND, PAGE, to more complex models, such as MERGE, WITCH, IMAGE, REMIND, TIMES and others (CarbonBrief, 2018). The former group represents climate and economy in a highly aggregated manner and explicitly models impacts from the climate change on the economy. These models have been developed to identify "optimal" climate policies and are suitable for conducting cost-benefit analysis under various policies or calculating the “social cost of carbon” (Weyant, 2017; CarbonBrief, 2018). The group of more complex models operate at a more disaggregated sectoral and/or regional levels and allow in some cases getting "projections of physical impacts such as reductions in crop growth, land inundated by sea level rise, and additional deaths from heat stress" (Weyant, 2017).

This research project focuses on modeling DAC and CCS in Ada-BaHaMa model (Bahn, 2010; Bahn et al., 2012, 2015). This model, which was developed at HEC Montréal, departs from DICE (Nordhaus, 1994, 2007) and augments it with explicit mitigation and adaptation. Now we expand it even further to cover DAC and CCS.

As mitigation, adaptation and DAC / CCS have not been studied together under most existing IAMs yet, this project will enrich the literature on IAMs related to the climate change and provide insights into the optimal combination of these strategies under various policy scenarios.

In order to incorporate the recent developments into Ada-BaHaMa, we review and re-calibrate its parameters. During calibration of the carbon-free economy, we use projections from the AD-MERGE (Bahn et al., 2019), a model by HEC Montréal researchers which also includes adaptation and mitigation.

The methodology of this project comprises of a review of scientific literature on IAMs related to DAC and CCS, data collection from open sources combined with mathematical modeling in GAMS software (**https://www.gams.com**).

This report is organized as follows. In the next section, we conduct literature review with a focus on DAC and CCS. Chapter 1 augments Ada-BaHaMa with components related to DAC and CCS and provides a complete model specification. Chapter 2 is devoted to the model calibration and parameterization of the CCS and DAC modules. Chapter 3 presents sensitivity analysis to changes in CCS and DAC parameters and explores an interplay between the policy options.

Literature review

The Paris agreement (2016) aims at *"holding the increase in the global average temperature to well below 2^oC above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5^oC above pre-industrial levels"*. According to 2018 IPCC Special Report on the impacts of global warming of 1.5^oC above pre-industrial levels, to ensure no or limited overshoot of the 1.5^oC target, anthropogenic CO_2 emissions should decline by about 45% from 2010 levels by 2030 and reach net zero between 2045 and 2055. To limit global warming to below 2^oC, CO_2 emissions should decline by about 25% by 2030 and reach net zero between 2065–2080 (Masson-Delmotte et al., 2018).

All pathways that limit global warming to 1.5^oC with small or no overshoot heavily rely on CDR, with projected use of it on the order of 100–1000 $GtCO_2$ over the 21st century (Masson-Delmotte et al., 2018). By the moment this IPCC report was prepared, only several published pathways analyzed CDR measures beyond BECCS and afforestation, so CDR volumes mentioned above mostly reflect projections of BECCS deployment. Given that only a few IAM scenarios that incorporated DAC were considered by IPCC in this report, such as Chen and Tavoni (2013); Marcucci et al. (2017); Strefler et al. (2018), IPCC recognizes that DAC potential in capping temperature increases at 1.5^oC has yet to be explored (de Coninck et al., 2018).

Once considered to be prohibitive, the estimated cost of DAC has sharply declined over the past decade drawing more attention to DAC as a promising negative emissions technology. For example, early estimates of DAC costs ranged from \$136/t CO_2 in Keith et al. (2006) to \$600/tCO_2 in Socolow et al. (2011) to \$1,000/tCO_2 in House et al. (2011)

but were expected to fall to \$300/tCO_2 by 2050 in the latter. More recent research of Keith et al. (2018) assesses levelized DAC costs to be in the range \$94-232/tCO_2. Estimates by Larsen et al. (2019) range \$124-325/tCO_2 while those of Fasihi et al. (2019) - EUR133-222/tCO_2. All researchers expect these costs to go down with learning-by-doing.

It should however be noted that DAC is still at its infancy. There are several companies worldwide trying to commercialize DAC, such as Carbon Engineering in Canada, Climeworks in Switzerland, Global Thermostat and Prometeus Fuels in the US, and several others (Wikipedia, 2020b). Currently, a Carbon Engineering pilot plant in British Columbia is able to extract about 1tCO_2/day (Keith et al., 2018), while one Climeworks facility can capture 900tCO_2/year for use in greenhouses and another can capture and bury in the underground basalt formations 50tCO_2/year (Tollefson, 2018). Global Thermostat offers a modular plant architecture – from a single module capturing 50MtCO_2/year to a 40-Module plant capturing 2,000MtCO_2/year (Global Thermostat, 2020). The potential uses for the captured CO_2 are production of synthetic fuels, carbonated drinks, in greenhouses etc.

To date, DAC has seen a limited attention in the IAMs, but it's growing. Among the simpler IAMs, Keith et al. (2006) integrated DAC in the DIAM (the Dynamics of Inertia and Adaptability Model) which also included mitigation and a conventional backstop technology (producing clean energy without carbon emissions at a constant marginal cost, for example, from solar energy). They found that DAC reduces the cost of a worst-case climate scenario since it decreases the need for near-term precautionary abatement. However, mitigation increases in the long-term due to decreasing marginal abatement costs.

The latest version of DICE - DICE2016R - allows for negative emissions, thus implicitly allowing CDR/DAC (Nordhaus, 2016b). DICE models mitigation as emissions control rate μ, or a share of industrial emissions that have been curbed/diverted from the atmosphere. As such, μ can represent either mitigation, or CDR, or their mixture. μ is capped at 1 until 2065 and then its upper bound is allowed to grow up to 1.2. Negative emissions kick in when emissions control rate exceeds 1, which happens in 2160 or 2240 in optimal tax and business-as-usual scenarios, but they are not allowed to go above 20%

of industrial emissions at a given time.

Rickels et al. (2018) implement a generic version of CDR in DICE. They consider several CDR variations that include CO_2 storage in a reservoir disconnected from those in the carbon cycle (e.g. underground) and storage in the deep ocean. They introduce CDR in the model with a quadratic cost function that takes cumulative CDR as an input:

$$CDRcost(CDR) = c_1 CDR + c_2 CDR^2 \tag{1}$$

To account for uncertainties in the cost of CDR when it's scaled to the gigaton levels, they explore a range of c_2 values corresponding to a marginal CDR cost at the first GtC at \$90-10,080/tCO_2.

Belaia (2019) includes CDR and solar geoengineering (SG) in DICE to explore the temporal sequence of mitigation, CDR and SG. To model CDR, she makes small tweaks to the model. She sets μ upper bound to 1 in scenarios without CDR and lifts this constraint in scenarios with CDR. She finds that SG is introduced together with mitigation, and once mitigation is exhausted, CDR reduces CO_2 concentrations leading to phasing out of SG.

With respect to other IAMs, Chen and Tavoni (2013) introduce DAC into the World Induced Technical Change Hybrid (WITCH) model which also includes CCS and BECCS. They use cost breakdowns and energy estimates for DAC presented in Socolow et al. (2011) and find out that DAC is an important technology to achieve a stringent climate objective of 490 ppm-eq but which is deployed after other main abatement options have been used up. The scale of DAC deployment could be on the level of hundreds of GtCO_2 by 2100 but alternative abatement options (e.g. more efficient CCS, higher decarbonization of mobile emission sources due to next-generation bio-fuels) would decrease DAC volumes. At the same time, DAC would not be profitable for a less ambitious climate objective (about 550 ppm-eq). Also, large scale deployment of DAC could result in a sharp decline of carbon concentrations in the atmosphere and subsequent CO_2 outgassing from the oceans.

Marcucci et al. (2017) introduce DAC in the MERGE-ETL model, that also includes

CCS and BECCS options, in order to explore scenarios limiting global warming to 1.5^oC and 2^oC. They assume DAC to be available from 2060 with an initial cost of \$600/tCO_2 captured and a floor cost of \$200/tCO_2. They find that the first, more stringent target, is achievable only when using DAC. DAC technology can help reach deep decarbonization goals and reduce mitigation costs with stringent targets. It also substitutes BECCS in the stringent scenarios.

Strefler et al. (2018) include CDR into the global multi-regional energy-economy climate model REMIND to determine cost-effective emission and technology pathways for 1.5^oC and 2^oC targets under Paris Agreement. They show that while following the nationally determined contributions until 2030 makes the latter target unachievable without CDR, ambitious mitigation significantly decreases the necessary CDR levels to reach Paris climate targets. Returning to 1.5^oC by 2100 requires a combination of ambitious near-term mitigation, high levels of CDR deployment, and fast CO_2 emission reduction.

Realmonte et al. (2019) compare role of DAC in two models: TIAM-Grantham and WITCH under 1.5^oC and 2^oC scenarios. They find that DAC deployment reduces near-term mitigation costs while complementing other negative emission technologies instead of substituting them. They point out that to capture 1.5 GtCO_2/year (levels estimated in their scenarios) would require significant amounts of sorbent production (and a refocusing of the chemical industry) along with a large need for electricity and heat. The global temperatures could overshoot the target by 0.8^oC in case it turns out that scaling of DAC is not possible. Therefore, authors suggest DAC should be deployed along with other mitigation options.

Bahn and Haurie (2020) propose a highly schematic game model of the asymptotic steady-state. The idea of the model is to explore behaviours of four coalitions of countries when they share a global emissions budget that is maintained thanks to negative emissions technologies. To ensure net-zero emissions of GHGs which steady state implies, they introduce CCS and DAC to Ada-BaHaMa model from which they also remove time dimension. They analyze a fully “cooperative” solution and a Nash equilibrium solution which involves international trading of emissions.

Keith et al. (2018) in their paper *A Process for Capturing CO_2 from the Atmosphere* provide detailed engineering and cost analysis for a 1 Mt-CO_2/year direct air capture plant. The costs include capital, operations and management and energy costs in terms of gas or gas&electricity. Authors calculate costs for the first as well as Nth plant (for which costs would have decreased due to learning-by-doing).

In 2019, Rhodium Group assessed the role DAC technology could play in the US response to climate change (Larsen et al., 2019). The authors provide detailed cost estimates for DAC technology and point out they have recently sharply declined. They estimate a levelized cost of capture from the atmosphere to be \$173-\$290/tCO_2 and \$124-\$325/tCO_2 for liquid- and solid-sorbent technology, respectively, and that is, for the first state-of-the-art, megaton scale DAC plant. In the future, they expect these costs to go down due to learning-by-doing. The formula used to estimate levelized costs is shown below:

$$Cost\ of\ capture = levelized\ capital\ costs + non\text{-}energy\ operating\ costs + energy\ costs \tag{2}$$

Larsen et al. (2019) also point out that the available geologic storage resources in the US are capable of storing about 500 years' worth of current annual US CO_2 emissions.

In 2019, the US National Academy of Sciences, Engineering, and Medicine published a book *Negative Emissions Technologies and Reliable Sequestration: A Research Agenda*. One of its chapters is devoted to DAC. It evaluates two DAC technologies - using liquid solvents or solid sorbents - and calculates material and energy balances for several potential energy sources (renewables, nuclear, natural gas, or coal). This chapter also provides cost and capacity estimates for each capture process (NASEM, 2019a). A separate chapter discusses carbon dioxide compression, transport, and geologic sequestration (NASEM, 2019b).

Apart from DAC, we also plan to add CCS to Add-BaHaMa. With regard to it, we conducted a brief literature review mainly to find the most recent cost estimates for this technology. Rubin et al. (2015) review recent studies and summarize cost estimates for

CCS in constant 2013 US dollars for several power plant systems. They break down costs to CO_2 capture (post-, pre- and oxy-combustion), transportation and storage costs.

Budinis et al. (2018) show the main hurdle to the CCS deployment in the near- and medium term is the cost rather than technical barriers. They point that widespread CCS adoption will be critical to meet climate targets set by the Paris Agreement if fossil fuels continue to be actively used throughout the century. They also conduct a literature review and collect cost of captured/avoided CO_2 for different process plants, capture technologies and storage solutions, cost of electricity, transport costs for onshore and offshore pipelines with different capacities, cost of storage for various storage sites, and capital and operating costs. They recalculate all the costs to 2015 US dollars.

Bui et al. (2018) conduct a comprehensive (100+ pages) review of carbon capture and storage: the current state-of-the-art, transport, utilisation and storage issues. They also provide a review of CCS in IAMs in relation to 1.5^oC and 2^oC scenarios.

Koelbl et al. (2014a) conducted a comprehensive review of CCS modeling with regard to 450ppm and 550ppm CO_2p-eq IPCC scenarios, corresponding to $1.5-1.7^oC$ and $2.0-2.3^oC$ temperature increases vs pre-industrial levels (according to Edenhofer et al. (2018)). The authors analyze and compare the results of 12 IAMs participating in the 27th round of the Energy Modeling Forum (EMF) with a focus on the role of CCS in long-term abatement. According to the paper, IAMs model CCS as a lump-sum add-on cost to the technology used or as separate capture/transport/storage costs, the latter allowing testing sensitivity of results to each cost component. Most IAMs assume that CCS investment costs develop according to an exogenous function (often declining) but only several have introduced endogenous learning.

We also explored the recent changes in the DICE as Ada-BaHaMa shares many parameters with this model. The revisions in the latest DICE2016R version are summarized in section 2.1.

Chapter 1

Model specification

In this section, we present the complete specification of the Ada-BaHaMa model and augment it with DAC and CCS components. The model specification below is mostly based on Ada-BaHaMa model as presented in Bahn (2010), Bahn et al. (2012) and Bahn et al. (2015). As this model itself was developed on a basis of the DICE model, some equations are borrowed directly from DICE (Nordhaus, 1994, 2007, 2016a).

1.1 Indices, parameters and variables

1.1.1 Indices

The following **indices** are used in the model:

$i = \{1,2,3,4\}$, which stands for carbon-intense economy, carbon-free economy, adaptation, and direct air capture (DAC), respectively

$E_i = \{1,2\}$, which stands for carbon-intense and carbon-free economy, respectively

$t \in T$, which stands for time periods (in **5-year** increments)

1.1.2 Parameters

The model uses the following **parameters**:

t_{step}: duration of one time period (**5 years**)

ρ: pure rate of social time preference (per year)

α_{mcu}: elasticity of marginal utility of consumption or rate of inequality aversion

δ_{Ki}: an annual depreciation rate of capital K_i

p_{Ei}: energy price in a given economy

$\phi_{Ei}(t)$: energy efficiency in a given economy at time t

$A(t)$: total factor productivity (TFP) of the Cobb-Douglas production function

α_i: the elasticity of output with respect to capital K_i (only for K_1 and K_2)

θ_i: the elasticity of output with respect to emissions E_i

$\psi_{11}, \psi_{12}, \psi_{21}, \psi_{22}, \psi_{23}, \psi_{32}, \psi_{33}$: parameters of the carbon cycle describing carbon flows per period, i.e. movements of carbon between atmosphere (index 1), upper and lower oceans (indices 2 and 3, respectively). The pair of indices shows the direction of carbon movements. For example, ψ_{12} shows the share of atmospheric carbon that gets absorbed in the upper ocean over the 5-year period while ψ_{21} shows the share of carbon contained in the upper ocean that returns back to the atmosphere over the same period

$M_{AT}(1750), M_{UP}(1750)$ and $M_{LO}(1750)$: equilibrium concentration of carbon in the atmosphere, upper and lower oceans, respectively, in 1750

$\xi_1, \xi_2, \xi_3, \xi_4$: parameters of the climate equations (flows per period) that describe relationships between radiative forcings, atmospheric temperature and temperature in the lower oceans

η: radiative forcing from doubling of atmospheric carbon concentrations (watts per square meter)

T_{2*CO_2}: equilibrium temperature impact from doubling of CO_2 concentrations (^oC per doubling CO_2)

T_d and cat_T: parameters of the damage function (explained later)

γ_1 and γ_2 are calibration parameters in the adaptation module referring to learning effect parameter and complementarity parameter, respectively

$\underline{\alpha_{AD_p}}$ and $\overline{\alpha_{AD_p}}$ (resp., $\underline{\alpha_{AD_r}}$ and $\overline{\alpha_{AD_r}}$): the minimum and maximum marginal proactive (resp., reactive) adaptation efficiency

β_{AD_p} and β_{AD_r}: scale values of the adaptation module

γ_{AD_p} and γ_{AD_r}: power values of the adaptation module

$cost_{CCS}$ and $cost_{DAC}$: levelized costs of CCS and DAC, respectively, in trillion dollars per Gt (10^9 tons) of CO_2[1] captured and stored

max_{CCS} : the maximum fraction of emissions that can be captured in the carbon-intense economy with CCS

max_{DAC} : the maximum amount of CO_2, in $GtCO_2$ per year, that can be captured with the DAC technology

e_2^{DAC} : emissions from the carbon-free energy used to power DAC, in $GtCO_2$ per $1GtCO_2$ captured from the ambient air

1.1.3 Variables

The model uses the following **variables**:

$AD(t)$ - fraction of damages at time t that still persists after adaptation measures, in % of total output

$C(t)$ - total consumption at time t, trillion (10^{12}) of 2010 U.S. dollars (further referred to as simply dollars)[2]

$c(t)$ - per capita consumption at time t, million dollars

$CCS(t)$ - amount of CO_2 captured at a source of origin at time t with the use of carbon capture and sequestration, in $GtCO_2$

$D(t)$ - damages from climate change, % of total output lost due to climate change

$DAC(t)$ - amount of CO_2 captured from an ambient air with the use of direct air capture (DAC), in $GtCO_2$

$E_1(t)$, $E_2(t)$ and $E_4(t)$ - yearly emissions of GHG, respectively, in the carbon-intense, carbon-free economy and DAC sector, at time t, in $GtCO_2$

[1] To simplify notation, we also use $GtCO_2$ to refer to the same value throughout this report.

[2] We attempt to have the same year dollars as in DICE2016R. The code of the latter mentions both 2010 and 2005 U.S. dollars, likely mistakenly. Our best guess this should be 2010 U.S. dollars.

$E_{land}(t)$ - yearly emissions of GHG from land use at time t, in $GtCO_2$ (determined exogenously)

$E(t)$ - total yearly emissions of GHG at time t, in $GtCO_2$

$ELF(t)$ - economic loss factor due to climate change at time t, which is the share of output remaining after subtracting climate change damages, in %

$F(t), F_{EX}(T))$ - increase in total and exogenous (for GHG other than CO_2) radiative forcings since 1900 (watts per square meter)

$I_i(t)$ - yearly investment in capital K_i at time t, trillion dollars

$K_1(t)$ and $K_2(t)$ - physical stock of productive capital, respectively, in the carbon-intense and carbon-free economy at time t, trillion dollars

$K_3(t)$ - physical stock of proactive adaptation capital K_i at time t, trillion dollars

$K_{3max}(t)$ - maximal stock of proactive adaptation capital K_3 at time t, trillion dollars

$L_i(t)$ - labour force allocated to the sector i of the economy at time t, in million persons $(i = 1,2,4)$

$M_{AT}(t)$, $M_{UP}(t)$, $M_{LO}(t)$ - mass of carbon in the atmosphere, upper ocean and lower ocean reservoirs, respectively, in Gt of carbon equivalent at the beginning of a period

$S_3(t)$ - the amount of reactive adaptation spending at time t, trillion dollars

$S_{3max}(t)$ - the maximum amount of adaptation spending that would ensure the optimal effectiveness of the reactive adaptation measures at time t, trillion dollars

$T_{AT}(t)$, $T_{LO}(t)$ - increase in global mean surface temperature and temperature of lower oceans, respectively, in ^oC since 1900

W - discounted welfare across all forecast horizon.

1.2 The objective function

The **objective function** seeks to maximize welfare across the whole foresight horizon:

$$\max \mathrm{W} = \sum_{t \in T} t_{step} e^{-\rho t} L(t) U(c(t)) \tag{1.1}$$

where $\rho = 0.015$ is pure rate of social time preference (per year), $L(t)$ is total labor (population) and $U(c(t))$ is utility of per capita consumption of goods and services at time t measured as:

$$U(c(t)) = \frac{c(t)^{1-\alpha_{mcu}}}{1-\alpha_{mcu}} \tag{1.2}$$

where $c(t) = \frac{C(t)}{L(t)}$ is per capita consumption at time t and $\alpha_{mcu} = 1.45$ is elasticity of marginal utility of consumption, or the rate of inequality aversion (Nordhaus, 1994, 2007).

When $\alpha_{mcu} \to 1$, this yields the logarithmic (Bernoullian) utility function (Nordhaus, 1994, p. 11-12):

$$U(c(t)) = \log(c(t)) \tag{1.3}$$

so equation 1.1 changes as follows:

$$\max \mathrm{W} = \sum_{t \in T} t_{step} e^{-\rho t} L(t) \log(c(t)) \tag{1.4}$$

Although the latter two formulations may have been used in some earlier Ada-BaHaMa versions, the current model specification uses Equations 1.1 and 1.2, similarly to DICE-2016.

1.3 Economic module

Ada-BaHaMa assumes that production happens in the carbon-intensive economy ($i = 1$) and carbon-free economy ($i = 2$). To model production, an extended Cobb-Douglas production function in three inputs, capital (K), labor (L) and energy (measured through

GHG emissions) is used:

$$Y(t) = A(t)[K_1(t)^{\alpha_1}(\phi_{E_1}(t)E_1(t))^{\theta_1(t)}L_1(t)^{1-\alpha_1-\theta_1(t)} + K_2(t)^{\alpha_2}(\phi_{E_2}(t)E_2(t))^{\theta_2(t)}L_2(t)^{1-\alpha_2-\theta_2(t)}] \tag{1.5}$$

where $A(t)$ is the total factor productivity, α_i is the elasticity of output with respect to capital K_i, ϕ_i the coefficient of energy efficiency of emissions (factor for converting emissions into energy), θ_i the elasticity of output with respect to emissions and L_i is labor employed in economy i (deemed proportional to the population).

Some earlier BaHaMa versions may have used two different parameters $A(t)$ for the carbon-intense and carbon-free economy. We however assume that the main difference between these two economies is in sources of energy they use to produce goods and services. However, once this energy has been transformed to the form of electricity and mixed up in the same grid, it's impossible to distinguish between its sources any more. So we keep a single value of productivity $A(t)$ for the whole economy.

Labor is divided across 3 sectors: carbon-intensive, carbon-free economy and DAC:

$$L(t) = L_1(t) + L_2(t) + L_4(t) \tag{1.6}$$

Accumulated capital changes according to the investment (I_i), measured annually, and an annual depreciation rate δ_{Ki} through a following relationship:

$$K_i(t+1) = t_{step}I_i(t) + (1-\delta_{Ki})^{t_{step}}K_i(t), i = 1,2,3. \tag{1.7}$$

1.4 Emissions, carbon cycle and climate module

We define yearly emissions as the sum of emissions from the carbon-intense, carbon-free economy, land use and powering DAC by low-carbon sources less the emissions captured by CCS at a source (and thus diverted from coming to the atmosphere):

$$E(t) = E_1(t) + E_2(t) + E_{land}(t) + E_4(t) - CCS(t) \tag{1.8}$$

When DAC is powered by carbon-intense energy, it is possible to capture CO_2 produced in the process and store it in geological formations together with the CO_2 captured from the ambient air. However, we assume that DAC will be powered by low-carbon energy, therefore, emissions from DAC activity, $E_4(t)$, won't be captured since the source of energy (and these emissions) will be situated away from DAC capacities.

When calculating carbon atmospheric concentrations, we subtract CO_2 volumes captured with DAC from total generated emissions:

$$M_{AT}(t+1) = t_{step}\frac{12}{44}(E_{tot} - DAC(t)) + \psi_{11}M_{AT}(t) + \psi_{21}M_{UP}(t) \tag{1.9}$$

where $\frac{12}{44}$ is the factor for converting CO_2 into C and parameters ψ describe carbon flow between different strata (see subsection 1.1.2).

We keep the following equations of the climate module the same as in Ada-BaHaMa and DICE, however, DAC and CCS impact CO_2 concentrations in the upper and lower ocean, radiative forcings and temperature indirectly through the two equations above.

$$M_{UP}(t+1) = \psi_{12}M_{AT}(t) + \psi_{22}M_{UP}(t) + \psi_{23}M_{LO}(t) \tag{1.10}$$

$$M_{LO}(t+1) = \psi_{23}M_{UP}(t) + \psi_{33}M_{LO}(t) \tag{1.11}$$

where ψ_{12}, ψ_{23} are constants and the other parameters are calculated as follows:

$$\psi_{11} = 1 - \psi_{12} \tag{1.12}$$

$$\psi_{21} = \psi_{12}\frac{M_{AT}(1750)}{M_{UP}(1750)} \tag{1.13}$$

$$\psi_{22} = 1 - \psi_{21} - \psi_{23} \tag{1.14}$$

$$\psi_{32} = \psi_{23}\frac{M_{UP}(1750)}{M_{LO}(1750)} \tag{1.15}$$

$$\psi_{33} = 1 - \psi_{32} \tag{1.16}$$

Atmospheric carbon concentration impacts radiative forcings:

$$F(t) = \eta log_2\frac{M_{AT}(t)}{M_{AT}(1750)} + F_{EX}(t) \tag{1.17}$$

where $M_{AT}(1750)$ is carbon concentration in the atmosphere in 1750 (in GtC), η is radiative forcing from doubling of atmospheric carbon concentrations and $F_{EX}(t)$ are radiative forcings from other GHG growing linearly from 0.5 in 2015 to 1 in 2100 (as shown in Table 2.1) and unchanging thereafter.

The following two equations describe the change in the earth's mean surface temperature and deep ocean's mean temperature, respectively:

$$T_{AT}(t+1) = T_{AT}(t) + \xi_1[F(t+1) - \xi_2 T_{AT}(t) + \xi_3(T_{AT}(t) - T_{LO}(t))] \tag{1.18}$$

$$T_{LO}(t+1) = T_{LO}(t) + \xi_4(T_{AT}(t) - T_{LO}(t)) \tag{1.19}$$

where $\xi_1, \xi_2, \xi_3, \xi_4$ are climate module parameters and ξ_2 is calculated as follows:

$$\xi_2 = \frac{\eta}{T_{2*CO_2}} \tag{1.20}$$

1.5 Damages and adaptation

Increasing global temperatures cause damages to the global production. Economic loss factor measures the share of total production that persists after we account for damages stemming from climate change:

$$ELF(t) = 1 - D(t) \tag{1.21}$$

Ada-BaHaMa defines damage function as follows:

$$D(t) = AD(t)(\frac{T_{AT}(t) - T_d}{cat_T - T_d})^2 \tag{1.22}$$

where T_d is the temperature increase from 1900 levels when damages start to occur and cat_T is the catastrophic temperature increase when no economic production would be possible any more.

Adaptation $AD(t)$ measures the fraction of damages remaining after application of reactive and proactive adaptation. Adaptation here is presented according to Bahn et al. (2015):

$$AD(t) = 1 - \alpha_{AD_p}(t)\frac{K_3(t)}{K_{3max}(t)} - \alpha_{AD_r}(t)\frac{S_3(t)}{S_{3max}(t)} \tag{1.23}$$

where $\alpha_{AD_p}(t)$ and $\alpha_{AD_r}(t)$ are proactive and reactive adaptation effectiveness. If $AD(t) = 1$, then $K_3(t)$ and $S_3(t)$ equal zero, and there is no adaptation, so 100% damages from the climate change persist. The following equations are part of the adaptation module:

$$K_{3max}(t) = \beta_{AD_p}(\frac{T_{AT}(t)}{T_d})^{\gamma_{AD_p}} \tag{1.24}$$

$$S_{3max}(t) = \beta_{AD_r}(\frac{T_{AT}(t)}{T_d})^{\gamma_{AD_r}} \tag{1.25}$$

$$\alpha_{AD_p}(t) = (\overline{\alpha_{AD_p}} - \underline{\alpha_{AD_p}})(\gamma_1\frac{K_3(t)}{K_{3max}(t)} + \gamma_2\frac{S_3(t)}{S_{3max}(t)}) + \underline{\alpha_{AD_p}} \tag{1.26}$$

$$\alpha_{AD_r}(t) = (\overline{\alpha_{AD_r}} - \underline{\alpha_{AD_r}})(\gamma_1\frac{S_3(t)}{S_{3max}(t)} + \gamma_2\frac{K_3(t)}{K_{3max}(t)}) + \underline{\alpha_{AD_r}} \tag{1.27}$$

where β_{AD_p} and β_{AD_r} are scale values, γ_{AD_p} and γ_{AD_r}power values, $\underline{\alpha_{AD_p}}$ and $\overline{\alpha_{AD_p}}$ (resp., $\underline{\alpha_{AD_r}}$ and $\overline{\alpha_{AD_r}}$) are the minimum and maximum effectiveness values for proactive (resp., reactive) adaptation, and γ_1 and γ_2 are calibration parameters ($\gamma_1 > \gamma_2$, $\gamma_1 + \gamma_2 = 0$).

1.6 CCS module

CCS refers to capturing CO_2 at a source of origin (e.g. at power plants) and then storing it in geological formations which should prevent its coming to the atmosphere. **We consider CCS as an add-on to the carbon-intense technology and model CCS by using a CCS cost per unit of CO_2 captured and stored.** CCS costs have been rather extensively explored in the literature and encompass levelized costs of carbon dioxide capture, costs of its transport from a source of origin to a storage site and storage costs themselves. Levelized capture cost expresses the system's lifetime cost in dollars per unit of emissions captured for the system to break-even. Such costs include capital investment, operational and maintenance costs, cost of fuel, if necessary. We review literature on CCS costs in section 3.1.

Capture, transportation and storage costs can be modeled separately to allow each cost component to follow its own (declining or growing) path and to measure sensitivity in CCS deployment to changes in different cost components. In the review by Koelbl et al. (2014a), 4 out of 12 IAMs considered in the paper modeled a single add-on cost, 5 modeled separately capture costs and combined transport/storage costs, and 3 modeled all costs separately. To keep our approach simple, **we will model CCS costs with a single parameter that lumps together all these costs:** $cost_{ccs}$. It will come into play when calculating consumption in Equation 1.37.

At earlier stages of this project, we had also considered modeling endogenous learning in CCS deployment leading to CCS capture component getting cheaper with growing cumulative CCS volumes:

$$cc_{ccs}(t) = cc_{ccs0}(1 - LR_{ccs})^{\frac{lnCCS_{cum}(t)}{ln(2)}} \tag{1.28}$$

where $cc_{ccs}(t)$ are levelized capture costs at a given time, $cc_{ccs}0$ are levelized capture costs at the initial time point, LR_{ccs} is the learning rate for doubling of CO_2 amounts captured with CCS and $CCS_{cum}(t)$ is the cumulative amount of CO_2 captured before the period t with the CCS technology. However, endogenous learning in CCS deployment is not widely used in other IAMs. Having considered this and given the aggregated high-level nature of Ada-BaHaMa that operates on gigaton scales (by reaching which CCS costs would have already declined), we decided not to proceed with this idea. For the same reason, we also keep $cost_{ccs}$ fixed over time, but we conduct a sensitivity analysis trying several cost levels.

When modeling CCS, we need to take into account that we cannot capture 100% emissions from the economy and set a corresponding upper limit in the model. First of all, we can capture CO_2 emissions only from the stationary sources in the carbon-intense sector such as electricity/heat producing plants and industry but not from the dispersed ones such as private buildings or transportation. Secondly, even for stationary sources, it's not possible to capture 100% of emissions at a given source due to technology limitations.

To account for both factors, we set a single constraint:

$$CCS(t) \leq max_{CCS} E_1(t) \tag{1.29}$$

where $CCS(t)$ is the amount of CO_2 captured per year (in $GtCO_2$) and max_{CCS} is the maximum fraction of emissions that can be captured in the carbon-intense economy.

This parameter can change over time, for example, grow if electric transport becomes more popular (while feeding on electricity coming from carbon-intense sources) or if there are advancements in the CCS technology that allow capturing higher rates of emissions. However, for simplicity, we will keep this parameter unchanged throughout our modeling horizon but will do some sensitivity analysis to its change.

One more thing to consider when modeling CCS is whether there is a physical limit to the amount of CO_2 that we could store. Most IAMs reviewed by Koelbl et al. (2014a) do not impose constraints on the volumes of CO_2 captured and stored with CCS, though some validate those volumes ex-post and/or allow transport and storage costs to grow with the total volume stored thus imposing an indirect constraint on storage use. In our model, we won't add any such explicit constraint and will check CCS volumes ex-post.

This approach makes sense since the latest research suggests that potential storage is vast. According to Budinis et al. (2018), *"A number of studies have compiled regional estimates of* CO_2 *storage resources to suggest that cumulative resources to be in the range of 10,000–30,000* $GtCO_2$ *including 1000Gt in depleted oil and gas reservoirs [67]. This suggests an abundance of storage capacity relative to demand over the century."*

An earlier study by Koelbl et al. (2014b) provides global storage cost-supply curves for optimistic and pessimistic scenarios which we reproduce in Figure 1.1. The figure implies there is a lot of storage available for a reasonable price, thus supporting our idea not to impose any constraints or introduce storage cost increases and check CCS volumes ex-post.

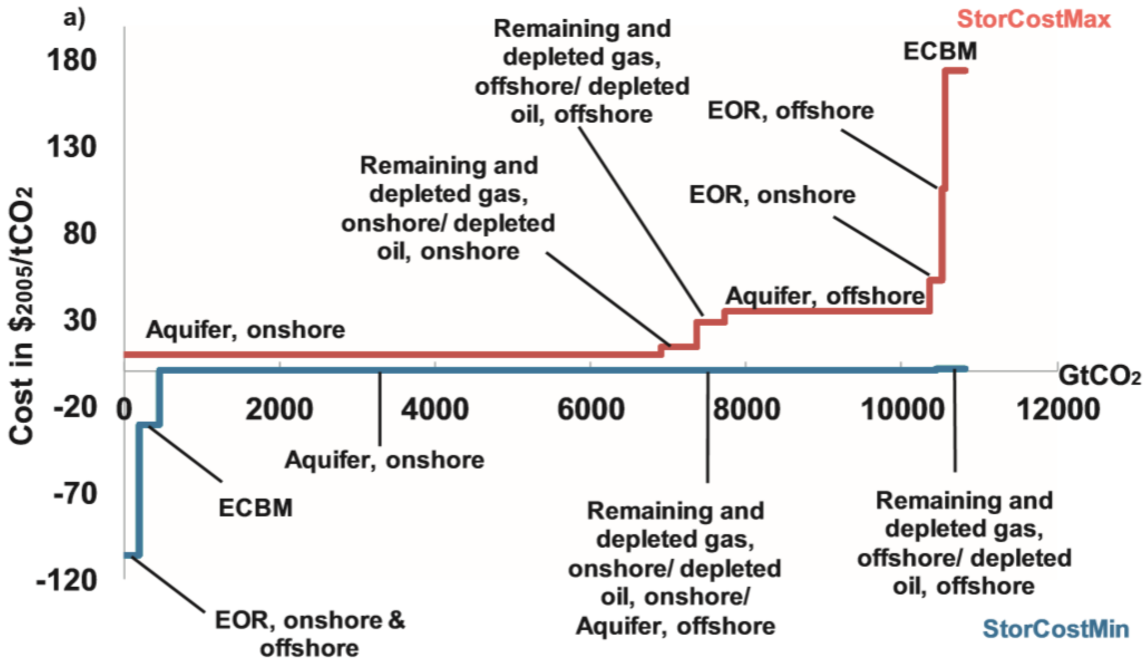

Fig. 3. Global storage cost-supply curves for high and low storage cost per reservoir type.

Figure 1.1: Cost of CO_2 storage as a function of the cumulative volume stored

1.7 DAC module

Over the course of this project, we've considered two approaches to DAC modeling. One is more complex and is based on the DAC capacities accumulation, similar to capital accumulation in the carbon-intense and carbon-free economy (Approach 1). The other is simpler and similar to that used in CCS modeling, when we model DAC with a levelized cost per unit of CO_2 captured and stored (Approach 2). For completeness, we provide the description of both approaches below. However, in the end, we stick to the simpler Approach 2 due to time constraints and difficulties in adequately modeling DAC energy consumption within Approach 1 in a simplified framework of Ada-BaHaMa (as its energy units are symbolic, and not real ones).

1.7.1 Modeling DAC capacities accumulation (Approach 1)

DAC is a capital-intense activity as it requires building new plants that could suck up CO_2 from the atmosphere. We assume that DAC capacities evolve similar to the capital in the economy with the same depreciation rate of 0.1:

$$DAC_{cap}(t) = (1 - \delta_{DAC})^{t_{step}} DAC_{cap}(t-1) + B_{DAC}(t-1) \tag{1.30}$$

where $DAC_{cap}(t)$ are DAC capacities available in period t (in $GtCO_2$/year), and $B_{DAC}(t-1)$ are DAC capacities built over the previous 5-year period (in $GtCO_2$/year).

According to Keith et al. (2018) and Larsen et al. (2019), DAC capacities cannot be used in full. Amount of CO_2 captured with DAC is thus limited to the fraction of available capacities:

$$DAC(t) \leq uDAC_{cap}(t) \tag{1.31}$$

where $DAC(t)$ is the amount of CO_2 captured from the atmosphere (in $GtCO_2$/year) and u - the utilization rate of available DAC capacities (0.9).

To convert DAC capacities built in a given period to investment costs, we use the following formula:

$$I_4(t) = B_{DAC}(t) \frac{I_{GtDAC}}{t_{step}} \tag{1.32}$$

where $I_4(t)$ is investment in DAC per year (in trillions dollars) and I_{GtDAC} - investments necessary to build plants with the total capacity of 1$GtCO_2$/year. Division by t_{step} is necessary because we split investments per 5-year period into annual ones.

We should note that papers exploring DAC focus on the nearest future and thus discuss much smaller scales of DAC deployment. In particular, the first state-of the-art plant is expected to have 1$MtCO_2$/year capacity. At the same time, in Ada-BaHaMa, we measure DAC in $GtCO_2$ captured and stored, to be in line with other variables (e.g. emissions, concentrations) in the model.

DAC technology also should get cheaper by learning-by-doing as more such DAC plants are built. Keith et al. (2018) provide cost estimates for the first and the N-th 1Mt-plants using a liquid-solvent technology and calculate that investment costs for them will amount \$1146mn and \$793mn, respectively. Larsen et al. (2019), in their turn, estimate investment costs for the first plant to be \$634-1711mn depending on the technology (liquid-solvent or solid-sorbent) and the cost scenario (\$1058mn, on average). They also use a learning curve with a learning rate of 10-15%, meaning DAC investment costs will decline by this amount after each doubling of DAC capacities. According to this learning curve, investment costs are expected to go down by 28% and 40% for 10% and 15% learning rates, respectively, after three doublings of DAC capacities, which refers to the 9th 1Mt-year plant.

Given this, we had considered accounting for learning-by-doing in Ada-BaHaMa. If we followed the approach of Larsen et al. (2019), we would need to multiply the right-hand side of equation 1.32 by a coefficient (≤ 1) that would reduce DAC investment costs depending on cumulative DAC capacities built up to that moment, as shown on Figure 1.2. However, given the aggregated nature of our model that operates at $GtCO_2$ scales and the fact that such a learning curve would add an important non-linearity to the model, we discarded this idea.

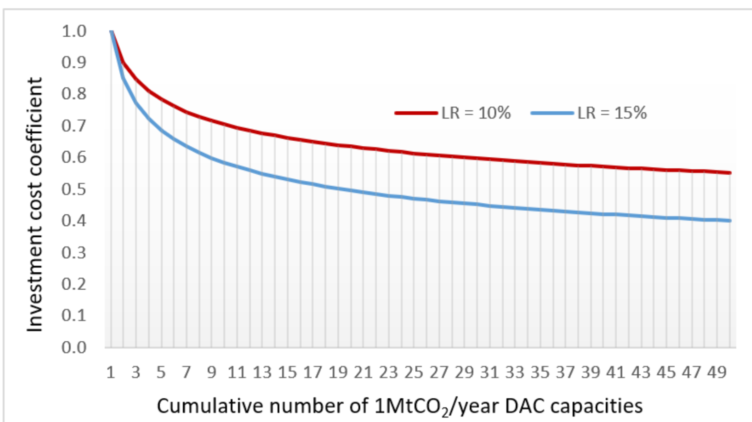

Figure 1.2: Investment cost as a function of cumulative DAC capacities

Apart from being a capital-intense activity, DAC also requires a lot of energy to power its plants, and these requirements differ for two major DAC systems: with liquid solvent and with solid sorbent. Depending on the potential source of energy, DAC will also produce additional emissions, and if these are emissions from the fossil fuel, they can normally be captured as well. Figure 1.3 shows energy requirements and additional CO_2 generated by DAC depending on the source of energy as presented in table 5.11 NASEM (2019a).

TABLE 5.11 Summary of Estimated Energy Requirements, CO_2 Footprint, and Carbon Capture for 1 Mt/y CO_2 Liquid Solvent and Solid Sorbent Direct Air Capture Systems

Direct Air Capture System	Energy Source		Energy Required ($GJ/t\ CO_2$)		CO_2 Generated ($Mt/y\ CO_2$)		Net CO_2 Avoided	Capture Cost ($\$/t\ CO_2$)	
	Electric	Thermal	Electric	Thermal	Electric	Thermal	($Mt/y\ CO_2$)	Cap-tured	Net Re-moved[a]
Liquid Solvent	NG	NG	0.74-1.7	7.7-10.7	0.11-0.23	0.47-0.66	0.11-0.42	147-264	199-357
	coal	NG	0.74-1.7	7.7-10.7	0.18-0.38	0.47-0.66	0-0.35	147-264	233-419
	wind	NG	0.74-1.7	7.7-10.7	0.004-0.009	0.47-0.66	0.34-0.53	141-265	156-293
	solar	NG	0.74-1.7	7.7-10.7	0.01-0.03	0.47-0.66	0.31-0.52	145-265	165-294
	nuclear	NG	0.74-1.7	7.7-10.7	0.01-0.02	0.47-0.66	0.32-0.52	154-279	173-310
	solar	H2[b]	11.6-19.8	7.7-10.7	0.01-0.03	0	0.99	317-501	320-506
Solid Sorbent[c]	solar	solar	0.55-1.1	3.4-4.8	0.0004-0.008	0.008-0.01	0.892-0.992	88-228	89-256
	nuclear	nuclear	0.55-1.1	3.4-4.8	0.002-0.004	0.004-0.005	0.91-0.994	88-228	89-250
	solar	NG	0.55-1.1	3.4-4.8	0.0004-0.008	0.22-0.30	0.70-0.78	88-228	113-326
	wind	NG	0.55-1.1	3.4-4.8	0.002-0.003	0.22-0.30	0.70-0.78	88-228	113-326
	NG	NG	0.55-1.1	3.4-4.8	0.07-0.14	0.22-0.30	0.56-0.71	88-228	124-407
	coal	coal	0.55-1.1	3.4-4.8	0.15-0.3	0.32-0.44	0.26-0.53	88-228	166-877

[a] Assuming the use of an oxy-fired kiln to provide heat from natural gas in the calcination process, leading to greater CO_2 production and hence lower cost of net CO_2 removal, using a basis of 1.3 Mt CO_2 for NG/NG, 1.2 Mt CO_2 for coal/NG. (NG = natural gas).
[b] Assuming all hydrogen is produced via electrolysis using near zero-carbon power.
[c] Scenarios range from 2-low to 4-high.

Figure 1.3: Estimated energy requirements, CO_2 footprint, and capture cost for 1 $MtCO_2$/year liquid solvent and solid sorbent DAC systems

For our implementation of DAC in Ada-BaHaMa, we assume that it will rely only on renewable energy to satisfy its energy requirements, since it does not make sense to use exhaustible resources to power it and to produce more emissions that also need to be diverted from the atmosphere and stored. Ada-BaHaMa expresses energy through emissions and their energy efficiency. Emissions produced by DAC will be only from the advanced clean economy and are calculated as follows:

$$E_4(t) = e_2^{DAC} DAC(t) \tag{1.33}$$

where e_2^{DAC} are emissions from the carbon-free energy used to power DAC, in $GtCO_2$ per 1$GtCO_2$ captured from the ambient air. To approximate this parameter, we will use energy requirements for a solid sorbent system powered by solar energy from Figure 1.3. Midpoint emissions of this system equal 0.013 $GtCO_2$ for each $GtCO_2$ captured.

Once we have emissions from DAC, we can also calculate energy costs required to power DAC. We do this directly in the consumption equation 1.36, similarly to energy costs in the carbon-intense and carbon-free economies. Apart from investment and energy costs, we need also to account for the operations&management and transportation&storage costs, which we do in the same Equation 1.36.

We can also calculate labor employed in DAC (in millions people):

$$L_4(t) = l_{DAC} DAC_{cap}(t) \tag{1.34}$$

where l_{DAC} is the number of workers (in millions) required per 1Gt/year DAC capacities. To calculate this number, we can use Larsen et al. (2019) estimates: *"we calculate maintenance costs as 3% of the total capital requirement and we calculate labor costs as 30% of maintenance cost"*. This transforms into 1058*0.03*0.3 = $9.52mn of labor cost per first 1 Mt plant per year. Assuming an average wage at such a plant being equal to that in Mining, Quarrying, and Oil and Gas Extraction ($64,710/year in the US, on average, in 2018 according to the U.S. Bureau of Labor Statistics), we estimate 147 workers are necessary per first 1Mt plant. If we assume that this labor requirement will go down with learning-by-doing similarly to investment costs, then for 1Gt scale, this number should go down by 65% if we apply a conservative learning rate of 10%. That will translate into 51 people necessary to operate a 1Mt/year DAC plant, or to 0.051mn people per 1Gt capacity when DAC is deployed at a gigaton scale.

Similarly to CCS modeling and relying on the same arguments (see subsection 1.6), we do not impose a constraint on the cumulative amount of CO_2 that we can store over the nearest 150 years. Larsen et al. (2019) are also optimistic regarding storage, at least in the US: *"the US has world-class, CO_2 geologic storage resources capable of permanently sequestering at least 2.4 trillion metric tons of CO_2.xii That's enough space to store nearly*

500 years' worth of current annual US CO_2 emissions". Though storage capacities might be binding in other regions, we will not account for this in our model and assume that DAC capacities will be placed in the most efficient manner where a cheap and vast storage exists.

To prevent DAC from deploying too rapidly, we, however, impose a constraint on the amount of CO_2 that can be captured and stored in a given period (in $GtCO_2$ per year):

$$DAC(t) \leq max_{DAC} \tag{1.35}$$

We don't know what such a limit could be, so we will test several values in a sensitivity analysis.

1.7.2 Modeling DAC with a lump-sum cost (Approach 2)

Using this approach, we model DAC costs with a single parameter $cost_{DAC}$ (in trillion dollars per $GtCO_2$ captured and stored). This parameter covers all DAC costs: capital, operations and management, compression, transportation and storage costs. We include it directly in a modified consumption equation 1.37. From the Approach 1, we also keep equations 1.33 and 1.35.

1.8 Consumption

Following the Approach 1 to DAC modeling, consumption of goods and services at each time period is whatever left from the output $Y(t)$ after we subtract from it investments in each capital type (carbon-intense, carbon-free economy, DAC, adaptation), intermediate energy consumption in carbon-intense and carbon-free economy and the DAC sector, the cost of CCS and the damages due to climate change.

$$C(t) = ELF(t)Y(t) - I_1(t) - I_2(t) - I_3(t) - S_3(t) - p_{E1}\phi_1(t)E_1(t) - p_{E2}\phi_2(t)E_2(t) - I_4(t) - p_{E2}\phi_2(t)E_4(t) - (om_{DAC} + ts_{DAC})DAC(t) - cost_{ccs}(t)CCS(t) \tag{1.36}$$

where om_{DAC} and ts_{DAC} are DAC operations&management costs[3] and costs of compression/transportation and storage, respectively.[4] $cost_{ccs}$ are CCS add-on costs including levelized capture costs, transport and storage costs, in trillion dollars per $GtCO_2$ captured and stored.

If the follow the Approach 2 to DAC modeling (which we stick to in this report), the consumption equation simplifies as follows:

$$C(t) = ELF(t)Y(t) - I_1(t) - I_2(t) - I_3(t) - S_3(t) - p_{E_1}\phi_1(t)E_1(t) - p_{E_2}\phi_2(t)E_2(t) - cost_{CCS}CCS(t) - cost_{DAC}DAC(t) \tag{1.37}$$

where $cost_{DAC}$ are DAC costs including levelized capture costs, transport and storage costs, in trillion dollars per $GtCO_2$ captured from the ambient air and stored in geological formations.

[3] Larsen et al. (2019) provide these costs separately for the solid-sorbent and liquid-solvent technology. On average, these costs are \$49mn per $1MtCO_2$ captured, for the 1st 1Mt-year DAC plant.

[4] Compression, transportation and storage costs, according to Larsen et al. (2019), equal \$18mn/Mt CO_2.

Chapter 2

Ada-BaHaMa update and calibration

In this chapter, we describe Ada-BaHaMa update and calibration which consisted of several steps:

1. Model update according to the DICE2016R changes.
2. Calibration of the carbon-intense economy in Ada-BaHaMa in order to reproduce DICE2016R counterfactual baseline.
3. Ada-BaHaMa damage function calibration against DICE2016R.
4. Calibration of the carbon-intense and carbon-free economy in Ada-BaHaMa in order to reproduce DICE2016R counterfactual baseline (discarded later).
5. Calibration of the carbon-free economy against AD-MERGE.

2.1 Review of DICE2016R changes and Ada-BaHaMa parameters update

Ada-BaHaMa was developed based on the DICE model and shares many parameters with it, especially with the DICE-2007 version. As DICE has seen several revisions (in 2013 and 2016), we review main changes in DICE2016R in order to implement them in AdaBaHaMa as well, whenever relevant. These changes can be summarized as follows:

- Starting from 2013 version, DICE operates in 5-year time steps instead of 10-year steps, as before (Nordhaus and Sztorc, 2013; Nordhaus, 2016b).
- The current version measures global output in purchasing power parity (PPP) as used by the IMF, instead of the World Bank figures. It also uses IMF growth concept: total growth rate is calculated as the weighted average of GDP of different countries, with their shares in nominal global GDP in a current year used as weights (Nordhaus, 2017b).
- The historical growth estimates and the projections of per capita output growth have been revised upwards. As a result, 2100 global GDP estimates grew by a factor of 3.5 since 1990 (Nordhaus, 2017a).
- Damage function (a quadratic function of atmospheric temperature) has been revised 60% up since 1992 (Nordhaus, 2017a). However, its coefficient decreased from 0.0028388 in DICE-2007 (Nordhaus, 2007) to 0.00236 in DICE2016R (Nordhaus, 2016b) making it less penalizing of higher temperatures.
- Non-CO_2 radiative forcings have been revised up vs the previous versions (2007, 2013) following projections used in the IPCC Fifth Assessment (Nordhaus, 2016a).
- To reflect the latest observations, the rate of decarbonization of economy has been revised upwards, meaning a more rapid decline in the CO_2-to-output ratio (largely driven by China). DICE2016R assumes decarbonization rate of 1.5% per year, i.e., CO_2/GDP ratio declines by 1.5% per year (Nordhaus, 2017b, 2016a).
- The climate module has been updated to reflect recent earth system models. The equilibrium climate sensitivity (ECS) was revised upwards, so equilibrium CO_2 doubling results in mean global warming of 3.1^oC instead of 3^oC in 2007 version (Nordhaus, 2016a).

- DICE2016R incorporates the latest research on the carbon cycle. While earlier DICE versions were calibrated to fit the short-run carbon cycle (the first 100 years), the latest one reproduces better the expected long-term (up to 4,000 years) dynamics of the carbon cycle in the larger models (Nordhaus, 2017b, 2016a). However, this change compromised the model's ability to accurately forecast short-term emissions/temperatures relationships, especially with regard to low-emission scenarios (Rickels et al., 2018).

  As we could see from brief experiments with the model, these changes in the carbon cycle result in CO_2 staying in the atmosphere longer and causing higher temperatures than, for example, in 2007 version which parametrization was extensively used in earlier versions of Ada-BaHaMa.

- Overall, according to Nordhaus (2016a), the DICE2016R temperature projection *"is slightly lower than the last version, is higher than most other IAMs for a baseline scenario, and is consistent with (although a little lower) than the IPCC RCP 8.5 ensemble average."*

The Ada-BaHaMa model we started working under in this project shared many equations and parameters with the DICE-2007 and DICE-1999. In particular, this was the model from Bahn et al. (2015) that did not contain geoengineering but contained mitigation (carbon-free economy) and reactive and proactive adaptation to the changing temperatures. Given the revisions in DICE2016R mentioned above, we implemented the following changes in Ada-BaHaMa before proceeding with its calibration:

- Time step decreased from 10 to 5 year increments.

- Emissions unit changed from GtC to Gt of CO_2 (however, concentrations are still measured in GtC).

- Initial values of endogenous variables updated to reflect actual 2015 values in DICE2016R: GDP, industrial carbon emissions, capital accumulation, carbon concentration in the air, upper and lower oceans, temperatures in the atmosphere and lower oceans.

- Climate model and carbon cycle parameters updated to match those of DICE2016R, along with carbon emissions from the changes in land use (exogenous variable) and exogenous forcings from other GHG than CO_2. We compare parameters from DICE-2007 and DICE2016R in Table 2.1. In parentheses, we provide respective parameter/variable names as they appear in GAMS code.

- Other parameters updated: population dynamics, total factor productivity.

	DICE-2007	DICE2016R	Change
Climate model parameters			
ξ_1 (c1)	0.220	0.1005	-54%
ξ_2 (lam = fco22x/t2xco2)	1.2667	1.1875	-6%
ξ_3 (c3)	0.300	0.088	-71%
ξ_4 (c4)	0.050	0.025	-50%
η (fco22x)	3.8	3.6813	-3%
T_{2*CO_2} (t2xco2)	3.0	3.1	3%
fex0 2000/2015 forcings of non-CO_2 GHG	-0.06	0.5	-
fex1 2100 forcings of non-CO_2 GHG	0.3	1.0	233%
Carbon cycle parameters			
ψ_{11} (b11)	0.8107	0.8800	9%
ψ_{12} (b12)	0.1893	0.1200	-37%
ψ_{21} (b21)	0.0972	0.1960	102%
ψ_{22} (b22)	0.8528	0.7970	-7%
ψ_{23} (b23)	0.0500	0.0070	-86%
ψ_{32} (b32)	0.0031	0.0015	-53%
ψ_{33} (b33)	0.9969	0.9985	0%
$M_{AT}(1750)$ (mateq)	596.4	588.0	-1%
$M_{UP}(1750)$ (mueq)	1143.9	360.0	-69%
$M_{LO}(1750)$ (mleq)	18340.0	1720.0	-91%
Initial states	**2005**	**2015**	
$M_{AT}(0)$ (MAT0)	808.8	851.0	5%
$M_{UP}(0)$ (MU0)	1,255.0	460.0	-63%
$M_{LO}(0)$ (ML0)	18,365.0	1,740.0	-91%

Table 2.1: Selected parameter values in DICE-2007 and DICE2016R

2.2 Calibration of carbon-intense economy in Ada-BaHaMa

Once the changes mentioned above were implemented, we proceeded to the model calibration. The first step was to calibrate the carbon-intense economy against the DICE2016R counterfactual baseline, i.e. the one that does not account for economic damages from the atmospheric temperature increase as if there were no damages at all. This scenario is produced with the first run of the DICE2016R model (Nordhaus, 2016b) from which we also removed constraint limiting the available fossil fuel resources (*fosslim*, maximum cumulative extraction of fossil fuels, that was set at 6,000 GtC).

This calibration step consisted in finding parameters that would allow Ada-BaHaMa model to reproduce as accurately as possible the dynamics of total production, emissions and, as a consequence, carbon accumulation and temperature increases in the DICE2016R counterfactual scenario. To achieve that, we assumed that the carbon-intense economy at the initial point (2015) includes current low-carbon power sources, such as nuclear, hydro, geothermal, solar, wind energy, as well as energy from biofuels and waste. In its turn, carbon-free economy would refer to new/advanced sources of energy, such as hydrogen, fuel cells etc. that have not become important sources of energy yet (Bahn et al., 2012).

This assumption allowed us to remove carbon-free economy from the model (since it is not deployed yet significantly) and focus on the calibration of the carbon-intense economy only. At this stage, adaptation was removed from the model as well. We also fixed energy price per unit of emissions in the carbon-intense economy at the same levels as in the initial Ada-BaHaMa model we started working with (Bahn et al. (2015)): $p_{E1} = 0.425$ throughout the whole calibration. So we concentrated on adjusting the following parameters:

$A(t)$ - TFP of the production function, defined as follows:

$$A(t) = \frac{A(t-1)}{1 - gA_0 e^{-(dgA)n}} \tag{2.1}$$

where gA_0 - initial growth rate for TFP per 5 years, dgA - decline in growth rate of TFP per

5 years, n - number of years since t_0. Calculation of $A(t)$ requires setting three parameters: A_0, gA_0 and dgA.

$\phi_{E_1}(t)$: energy efficiency of carbon-intense economy at time t, defined as follows:

$$\phi_{E_1}(t) = \frac{\phi_{E_1}(0)e^{(\frac{-g\phi_{E_1}(0)}{dg\phi_{E_1}}e^{-dg\phi_{E_1}\frac{t}{2}})}}{e^{\frac{-g\phi_{E_1}(0)}{dg\phi_{E_1}}}} \tag{2.2}$$

where $\phi_{E_1}(0)$ - initial value for EE, $g\phi_{E_1}(0)$ - initial value for growth rate of EE, $dg\phi_{E_1}$ - rate of decrease for growth rate of EE.

It is important to note that given Ada-BaHaMa formulation, **we adjust $A(t)$ mostly to calibrate the total production $Y(t)$ while adjusting $\phi_{E_1}(t)$ helps us calibrate emissions from the carbon-intense economy $E_1(t)$**.

The magnitude of $A(t)$ in DICE2016R changed significantly vs DICE-2007 which was due to a slight reformulation of the production function $Y_{GROSS}(t)$ (Nordhaus, 2016b, 2007). If the earlier version of DICE production function contained $L(t)$ as is, the latter one included it as $L(t)/1000$. This was the main, but not the only, factor behind A_0 increase from 0.02722 in DICE-2007 to 5.115 in DICE2016R.

The calibration steps at this stage can be described as follows:

1. Run Ada-BaHaMa and DICE2016R counterfactual scenario in GAMS, collect solutions from both models and compare them. At this moment, discrepancies between two models are huge, especially with respect to CO_2 emissions (they were over-predicted by 77%, on average) and all the variables that depend on them.

2. Reformulate $Y(t)$ in Ada-BaHaMa (the equation 1.5 above) according to DICE2016R to use new $A(t)$ parameters from DICE2016R:

$$\begin{aligned} Y(t) = A(t)[K_1(t)^{\alpha_1}(\phi_1(t)E_1(t))^{\theta_1(t)}(\frac{L_1(t)}{1000})^{1-\alpha_1-\theta_1(t)} + \\ K_2(t)^{\alpha_2}(\phi_2(t)E_1(t))^{\theta_2(t)}(\frac{L_2(t)}{1000})^{1-\alpha_2-\theta_2(t)}] \end{aligned} \tag{2.3}$$

3. Reproduce in Excel Ada-BaHaMa equations for carbon-intense economy only (i.e. for the production function, only the first part of the right-hand side of equation

2.3). Use $I(t)$, $E(t)$ from DICE2016R counterfactual baseline solution and DICE parameters $L(t)$, $E_{land}(t)$ and $A(t)$ as an input to this model. So far, use $\phi_{E1}(t)$ from an old Ada-BaHaMa model.

4. Calculate $Y(t)$ for Ada-BaHaMa in Excel. Compare it to $Y_{GROSS}(t)$ in DICE solution and calculate **mean absolute percent error** ($MAPE$) between two data series for the whole Ada-BaHaMa estimation horizon:

$$MAPE = 100\frac{1}{T}\sum_{t=1}^{T}|\frac{Y(t)-Y_{GROSS}(t)}{Y_{GROSS}(t)}| \tag{2.4}$$

5. Using Excel Solver, solve for A_0, gA, dgA while minimizing $MAPE$. Since $Y_{GROSS}(t)$ grows almost 30 times between 2015 and 2215, absolute differences between the two series may become more pronounced with time. Using $MAPE$ punishes the **percent deviation** between series equally across all foresight horizon, which would not be the case if we minimized, for example, mean square error (MSE) between too series. It would put more weight on higher absolute discrepancies between two series which happen later in time at a cost of short-term discrepancies.

6. Re-scale A_0, using the original Ada-BaHaMa production function that contains $L(t)$ instead of $L(t)/1000$ (see equation 1.5) and all inputs to it from DICE2016R at $t = 0$. We also fix $Y(0)$ at a level we got after optimizing A_0 at the previous step. Re-scaling can be done analytically or using Excel Solver.

7. Changing A_0 and keeping gA and dgA fixed results in a whole new $A(t)$ series for Ada-BaHaMa, which nonetheless reproduces $A(t)$ **dynamics** from DICE quite accurately. If we plug these new values $A(t)$ into Ada-BaHaMa Excel model again, the discrepancy between $Y(t)$ and $Y_{GROSS}(t)$ (MAPE) that we minimized above grows. This happens because we have removed coefficient $1/1000$ before $L(t)$ which had a varying multiplicative effect on $Y(t)$ over time as it was raised to a changing power (caused by variation of $\theta_1(t)$).

8. Fix $A(t)$ and use Excel Solver to find $\phi_{E_1}(0)$, $g\phi_{E_1}(0)$ and $dg\phi_{E_1}$ to minimize MAPE. Up to this point, we did not calibrate $\phi_{E_1}(t)$ values.

9. Plug these preliminary calibrated values of $\phi_{E_1}(t)$ and $A(t)$ into Ada-BaHaMa and run a model in GAMS. Now the discrepancies between two series (as measured by MAPE) declined. However, emissions and other variables they affect still deviated much from DICE2016R (on average, we overshoot emissions by 20%).

10. Calibrate $\phi_{E_1}(0)$ in GAMS. For the moment, we forget about $g\phi_{E_1}(0)$ and $dg\phi_{E_1}$ and concentrate on $\phi_{E_1}(0)$ only. Taking $\phi_{E_1}(0)$ value from the optimization in Excel (0.2981), we change it little by little in GAMS until $E_1(t_0)$ in Ada-BaHaMa becomes reasonably close to that in DICE2016R. For each value of $\phi_{E_1}(0)$ tried, we note $E(t_0)$ and its discrepancy from the DICE2016R value. Declining discrepancy means that the change in $\phi_{E_1}(0)$ was in the correct direction, which helps narrowing down the parameter value ranges we try. In the end, we get $\phi_{E_1}(0)$= 0.3529, and from now on, we will keep it fixed.

11. Calibrate $g\phi_{E_1}(0)$ and $dg\phi_{E_1}$ using GAMS while keeping $\phi_{E_1}(0)$ and $A(t)$ fixed. The approach used is similar to the calibration of $\phi_{E_1}(0)$, but this time we look at the whole trajectory of emissions for the next 150 years and its deviation from emissions in DICE2016R (the same MAPE criterion can be used). We also have to tune two parameters now, therefore, the task of finding optimal parameters becomes more complex.

    It is important to note that DICE2016R assumes high rate of economy decarbonization. In particular, CO_2 to output ratio (measured in kg CO_2 per one dollar of output, in 2005 U.S. dollars) is assumed to decline 1.5% per year (Nordhaus (2016a)). This model parameter underwent significant revision compared with the earlier DICE versions. It produces a sharp exponential decline in emissions per unit of output that results in parabolic trajectory of emissions over the foresight horizon: emissions grow until 2130 and decline thereafter (see Figure 2.1).

To model such a steep economy decarbonization (dematerialization) and the related emissions pattern in Ada-BaHaMa, we had to reconsider $\phi_{E1}(t)$ dynamics and allow it to grow exponentially, and not logarithmically, as before. Again, we started with $g\phi_{E_1}(0)$ and $dg\phi_{E_1}$ values obtained at the step 8 and changed them little by little in GAMS until we got CO_2 emissions pattern that reproduced reasonably well that of DICE2016R.

After some experimenting with changing both parameters and exploring the resulting $\phi_{E1}(t)$ dynamics in Excel, we learnt that the rate of decrease for growth rate of EE ($dg\phi_{E_1}$) was mostly responsible for the "sharpness" of the EE curve: when it is small (large), the growth in $\phi_{E_1}(t)$ is steeper (slower). So we first found a value of $dg\phi_{E_1}$ that brought emissions pattern from Ada-BaHaMa to that of DICE2016R close enough while fixing the other parameter. Once this was done, we fixed $dg\phi_{E_1}$ and fine-tuned initial value for the growth rate of EE ($g\phi_{E_1}(0)$).

12. Once parameters related to the energy efficiency were calibrated, we fixed them and slightly adjusted parameters determining $A(t)$.

Table 2.2 shows parameters evolution at different steps of the calibration process described above. As we can see on the Figure 2.1, after the calibration, the output from Ada-BaHaMa model (with the carbon-intense economy only, no damages and adaptation) matches well the output of the DICE2016R counterfactual baseline.

Parameter	Step 1	Step 5	Step 6	Step 8	Step 10	Step 11	**Step 12 (final)**
A_0	5.115	**5.042**	**0.0566**	0.0566	0.0566	0.0566	**0.0577**
gA_0	0.0760	**0.0714**	0.0714	0.0714	0.0714	0.0714	**0.0708**
dgA	0.0050	**0.0045**	0.0045	0.0045	0.0045	0.0045	**0.00495**
$\phi_{E_1}(0)$	0.201	0.201	0.201	**0.2981**	**0.3529**	0.3529	0.3529
$g\phi_{E_1}(0)$	0.200	0.200	0.200	**0.1474**	0.1474	**0.1555**	0.1555
$dg\phi_{E_1}$	0.300	0.300	0.300	**0.0576**	0.0576	**0.004**	0.004

Table 2.2: Parameter values at different steps of counterfactual baseline calibration.

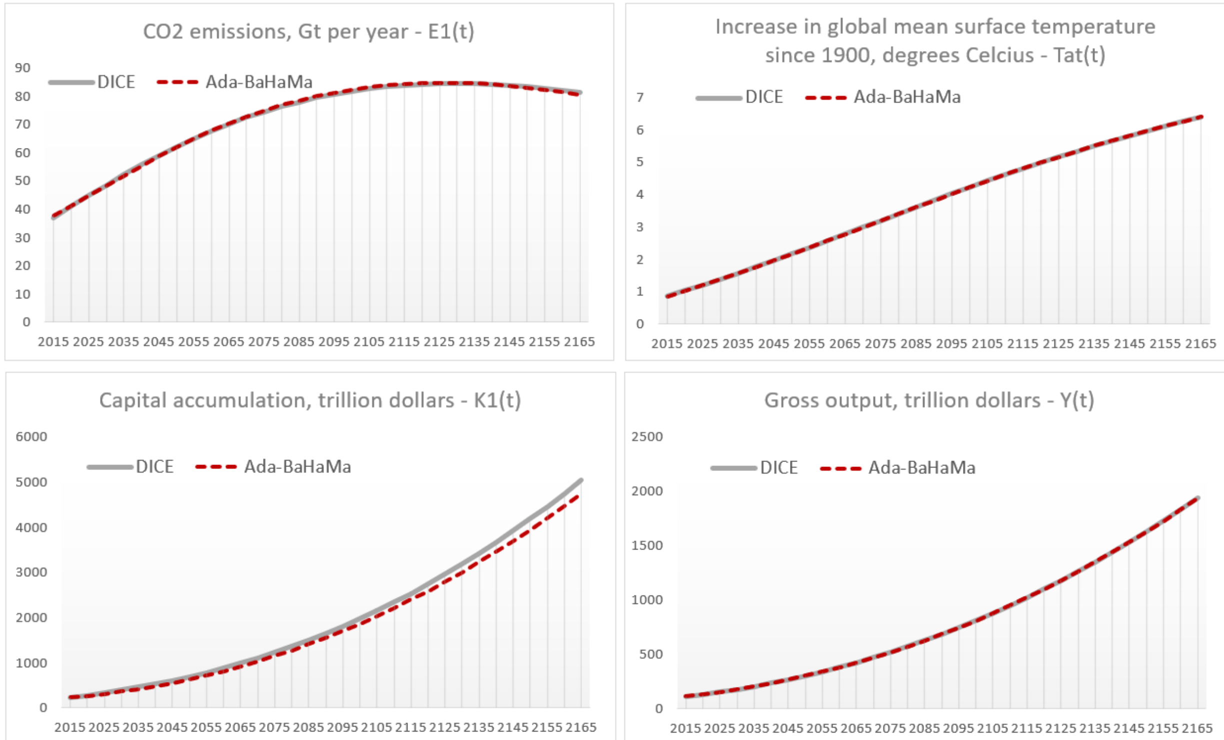

Figure 2.1: Dynamics of main variables in DICE2016R and Ada-BaHaMa counter-factual baseline after calibration

2.3 Damage function calibration

Once we calibrated the counterfactual baseline scenario, we proceed to the calibration of the Ada-BaHaMa damage function (see equation 1.22) since its formulation differs from that in DICE2016R:

$$D(t) = 0.00236 T_{AT}(t)^2 \tag{2.5}$$

We cannot replace the original Ada-BaHaMa damage function formulation with equation 2.5 because adaptation in Ada-BaHaMa is linked to this original formulation (1.22). If we change this formulation, we also have to re-calibrate adaptation. It is much simpler to calibrate parameters in the Ada-BaHaMa damage function so that it reproduces damages of the DICE damage function as close as possible.

We used the following steps to accomplish this in Ada-BaHaMa:

1. Take the calibrated counter-factual baseline with the carbon-intense economy only, enable damages from temperature increase, disable adaptation.

2. Run the model with the DICE damage function in GAMS.

3. Run the model with the Ada-BaHaMa damage function in GAMS.

4. Compare temperature $T_{AT}(t)$ and damages $D(t)$ dynamics produced in steps 2-3.

5. Take $T_{AT}(t)$ series from the output in the step 2. In Excel, calculate damage according to DICE and BaHaMa damage functions. We use $T_{AT}(t)$ from the output estimated with the DICE damage function since we would like to reproduce the link between temperature increase and damage from DICE in Ada-BaHaMa.

6. Calculate deviation between two series of damages calculated at step 5 with the use of MAPE function:

$$MAPE = 100\frac{1}{T}\sum_{t=1}^{T}|\frac{D_{Ada-BaHaMa}(t) - D_{DICE2016R}(t)}{D_{DICE2016R}(t)}| \tag{2.6}$$

7. Minimize MAPE using Excel solver, fixing T_d (the temperature increase from 1900 levels when damages start to occur) at the current level (0.106) but allowing cat_T (the catastrophic temperature increase when no economic production would be possible any more) to vary. Fixing T_d is important since adaptation is linked to this parameter. We get a value of $cat_T = 20.19$ instead of 16.10 in previous versions of Ada-BaHaMa.

8. Run the model in GAMS with the Ada-BaHaMa damage function and a new value of cat_T, compare the output to that from step 2. Before, using Ada-BaHaMa damage function resulted in lower emissions and higher damages compared to the use of the damage function from DICE (keeping all other parameters fixed). After the calibration, outputs from both functions match well (see Figure 2.2).

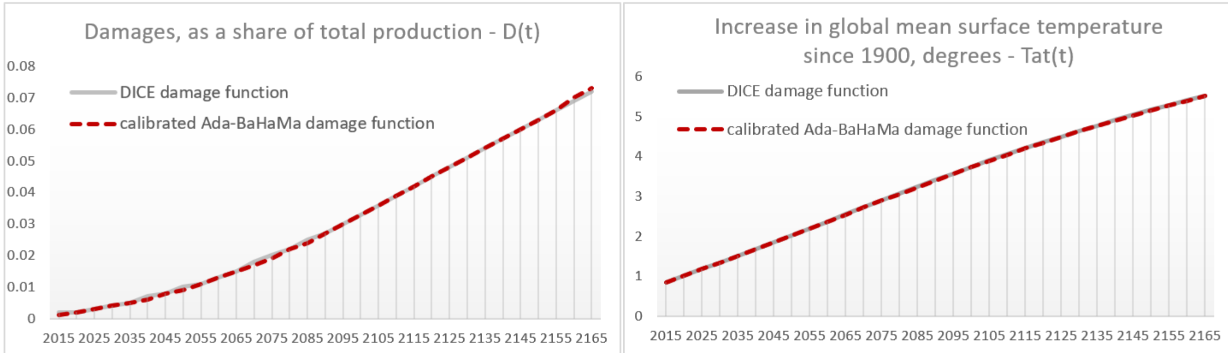

Figure 2.2: Trajectories of damages and atmospheric temperatures after calibration of Ada-BaHaMa damage function

2.4 Including low-carbon economy into the counter-factual baseline scenario

It is important to note that we calibrated the carbon-intense economy in the section 2.2 above using the traditional Ada-BaHaMa interpretation of what energy sources belong to the carbon-intense as opposed to low-carbon/carbon-free economy:

- carbon-intense energy includes all fossil fuel sources along with low-carbon power sources that are not in their infancy, such as nuclear, hydro, geothermal, solar, wind energy etc.;
- low-carbon/carbon-free energy refers to advanced sources of energy, such as hydrogen, fuel cells etc. that are being developed now and have not become important sources of energy yet.

We were not satisfied with this interpretation since low-carbon sources already produce a significant share of energy consumed in the world. Using data from the IEA World Energy Balances 2018 (IEA, 2019), we calculated that 18.5% of total primary energy supply in 2015 came from low-carbon/renewable sources such as nuclear (4.9%), hydro (2.5%), geothermal, solar and wind (1.5%), bio-fuels and waste (9.6%). With this in mind, we assumed that these sources already power low-carbon economy at the initial time point and tried to re-calibrate Ada-BaHaMa that contained both carbon-intense and low-carbon economy against the same counter-factual baseline from DICE2016R.

An attempt to calibrate Ada-BaHaMa in this setting lead to an important conclusion. **In the counterfactual baseline scenario, if there is even the slightest difference in prices of energy in the carbon-intense and low-carbon economy (for example,** $p_{E1} = 0.425$ **and** $p_{E2} = 0.4255$**), there is no investment in the latter and its share in total production tampers off to zero by 2050.** This happens consistently from run to run, no matter how we change energy efficiency of emissions in both economies, even if we select parameters that result in a very slow growth of $\phi_{E_1}(t)$ and exponential growth of $\phi_{E_2}(t)$.

Since we don't account for damages in this scenario, reducing emissions with the clean energy does not lead to higher welfare that we're trying to maximize (which would be the case if we accounted for damages), and there is no justification for paying even a little more for the clean energy. **So the Ada-BaHaMa model will consistently converge to solutions with the fast decay of the share of low-carbon economy in total production** (unless we set the price of energy equal in both economies). If we interpret low-carbon economy as the one powered by new/advanced sources of energy and assume that it's not present at the initial time point (as we did in section 2.2), it will never appear in the model solution given the slightest energy price differential in both economies.

We could interpret this model behaviour in the counter-factual baseline as follows (though we realize this interpretation is far fetched). If, for example, there appears a scientific proof that the higher levels of greenhouse gases do not lead to temperatures increase, there is no need to support and develop clean energy if it is even a bit costlier than the fossil fuel energy, so we end up in a world where only the latter is used.

Given the model behaviour described above, calibrating it against the counterfactual baseline **results in re-calibration of the carbon-intense economy but does not help us find the best parameters for the low-carbon economy** since we have almost no control over its dynamics. We describe a step-by-step calibration in this setting in **Appendix A** and compare the parameters obtained against those in section 2.2 in Table 2.3.

Figure 2.3 plots the Ada-BaHaMa output resulting from this calibration against DICE2016R counter-factual baseline. This time, emissions deviate more from DICE2016R values, however, this has little impact on temperature dynamics. On average, it deviates within 2% from DICE temperatures. **However, we won't use this calibration in the future work and advice against it due to the reasons explained above.**

Parameter	Carbon-intense economy only	Carbon-intense and low-carbon economy
$\phi_{E_1}(0)$	0.3529	0.2911
$g\phi_{E_1}(0)$	0.1555	0.1920
$dg\phi_{E_1}$	0.004	0.0211
$\phi_{E_2}(0)$	–	7.2764
$g\phi_{E_2}(0)$	–	0.1920
$dg\phi_{E_2}$	–	0.0211

Table 2.3: Final parameter values in the first and second Ada-BaHaMa calibration against the counter-factual baseline

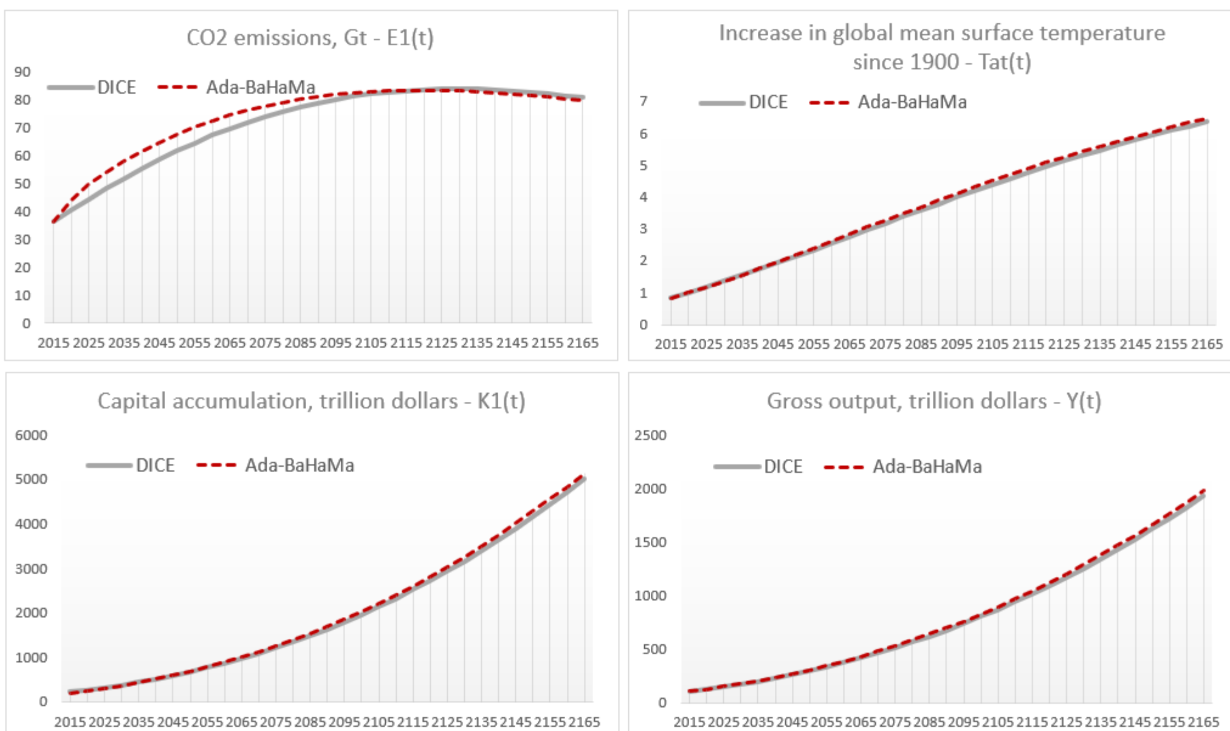

Figure 2.3: Dynamics of main variables in DICE2016R and Ada-BaHaMa counter-factual baseline after calibration of carbon-intense and low-carbon economy

2.5 Calibrating carbon-free economy on AD-MERGE

Since it is not possible to calibrate the carbon-free economy in the counter-factual baseline scenario (see section 2.4), we return to the previous interpretation of this economy as an advanced clean/hydrogen economy and will be calibrating it on AD-MERGE. The share of this economy at the initial time point is therefore close to zero, but it is supposed to grow in the future to mitigate damages as the atmospheric temperature increases. According to the AD-MERGE model (Bahn et al., 2019), advanced energy appears around 2030 and then steadily grows (scenario without adaptation PTONA-M). Its dynamics can be approximated with a linear trend (see Figure 2.4).

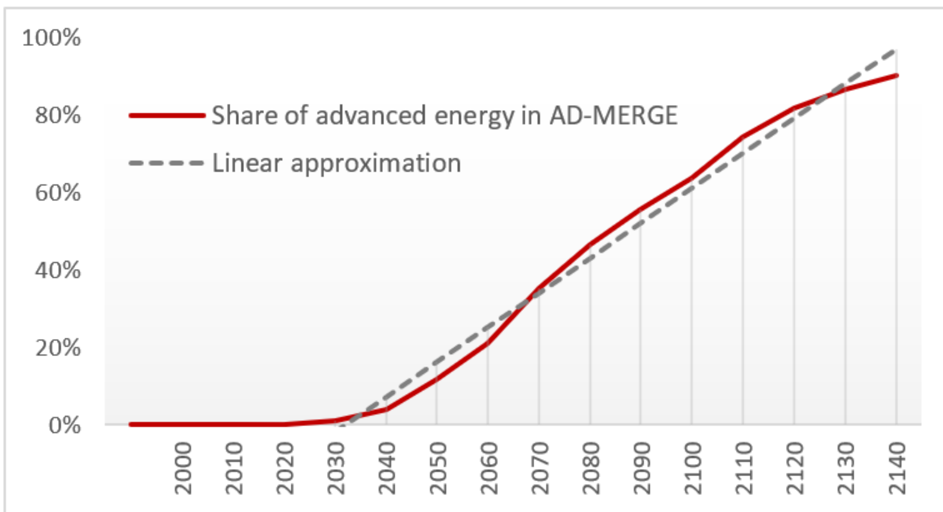

Figure 2.4: Share of advanced clean energy in total energy consumption in AD-MERGE

In this calibration, we will be adjusting the energy efficiency and energy price in the advanced clean economy. We start with the parameters in Table 2.4. They mostly come from the Table 2.2, and for parameters behind $\phi_{E_2}(t)$, we make the same assumptions as in section 2.4 (see p. 4 and 7 in Appendix A for detail). The energy efficiency of two economies at the initial time point is related as follows:

$$\phi_{E_2}(0) = 29.56\phi_{E_1}(0) \tag{2.7}$$

We also assume the same dynamics of energy efficiencies of emissions in both economies, which is equivalent to setting $g\phi_{E_1}(0) = g\phi_{E_2}(0)$ and $dg\phi_{E_1} = dg\phi_{E_2}$.

Parameter	Carbon-intense economy	Carbon-free economy
$\phi_{E_i}(0)$	0.3529	10.43
$g\phi_{E_i}(0)$	0.1555	0.1555
$dg\phi_{E_i}$	0.004	0.004
p_{Ei}	0.425	0.55

Table 2.4: Initial values of parameters for the calibration of the carbon-free economy

Before proceeding with this calibration, we run several experiments in GAMS to explore sensitivity of the capital share in the carbon-free economy to the change of its energy prices and energy efficiency. We enable damages (calibrated to DICE2016R) and carbon-free economy, disable adaptation, and try combinations of the following parameter values: $p_{E2} = \{0.55, 0.58, 0.60\}$ and $\phi_{E_2}(0) = \{5.215, 10.43, 20.86\}$[1].

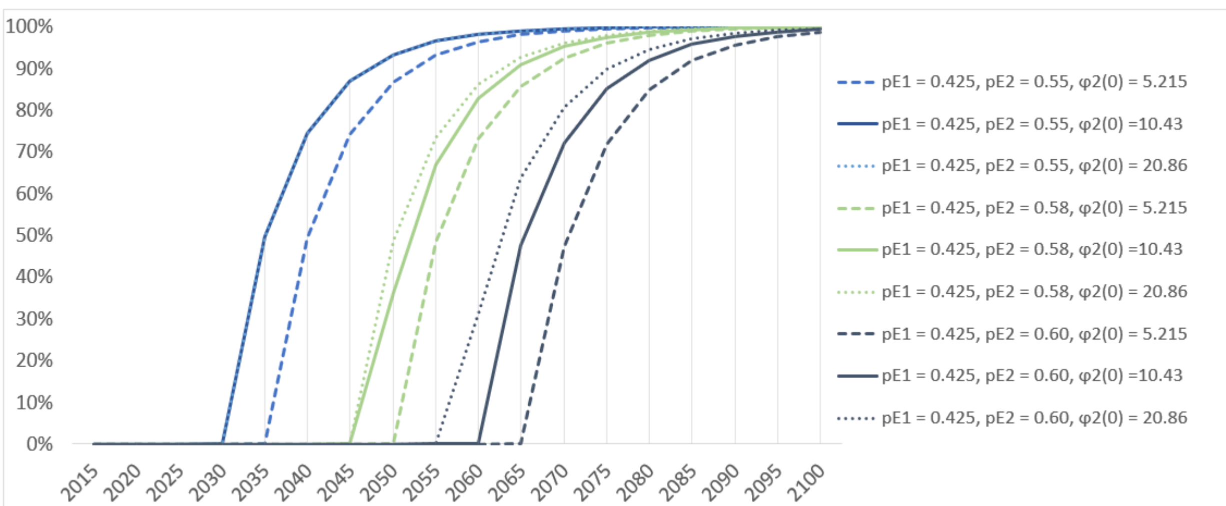

Figure 2.5: Dynamics of the share of advanced clean capital in total productive capital under different parameter values in Ada-BaHaMa

The share of clean capital under combinations of these parameters is shown on the Figure 2.5. Our findings can be summarized as follows:

[1] Using $\phi_{E_2} = 5.215$ (resp. $\phi_{E_2} = 20.86$) allows us decrease twice (resp. double) the EE of the carbon-free economy across all horizon compared to the initial value of 10.43.

1. The share of the carbon-free economy is very sensitive to the change of energy price in this economy. Increasing it by 9% (from 0.55 to 0.6) delays debut of the carbon-free economy by 25-30 years. In fact, this price (or rather the price differential between carbon-free and carbon-intense energy) to a high extent "decides" when the carbon-free economy starts to appear, shifting the curve along the X axis.

2. Once the carbon-free economy appears, its share skyrockets to about 90% within 20 years, provided no market penetration constraint for the carbon-free economy is used. Changing EE of the carbon-free economy does not make this growth less steep, even if we allow EE in the carbon-free economy to grow much slower than in the carbon-intense one (not shown on the plot).

3. The share of the carbon-free economy is much less sensitive to changes in its energy efficiency than in price. For example, decreasing EE twice vs the initial level (dashed lines on the Figure 2.5) results in its appearance 5 years later (compare dashed lines to the solid lines), while increasing it twice does not impact the moment it appears in 2 scenarios out of 3 (compare dotted lines vs solid lines; for $p_{E2} = 0.55$, two curves coincide). Even if we set $\phi_{E_2} = 100$ which is almost 10-fold higher than in Table 2.4 while keeping $p_{E2} = 0.55$, the dynamics of carbon-free capital share effectively coincide with that for $\phi_{E_2} = 10.43$ (blue solid line).

   We also tried doubling/decreasing by half $g\phi_{E_2}(0)$ (this makes EE in the advanced/-clean economy grow faster/slower than in the carbon-intense economy), or even keeping it flat throughout all the foresight horizon, but this did not change much the dynamics of the carbon-free capital share.

We thus conclude that **it's mostly the price of the clean energy that "decides" when carbon-free economy will emerge, while its energy efficiency impacts this to a much smaller extent**.

With this in mind, we conducted multiple attempts to calibrate advanced clean economy in Ada-BaHaMa against AD-MERGE. However, none of our attempts was satisfactory in all regards given the simplistic nature of Ada-BaHaMa and the latest updates to DICE parameters. For example, approximating well the dynamics of clean capital resulted in way too high temperature increases in 2100 (above 3^oC vs 1900), no matter how high energy efficiencies for the clean economy we tried (10, 100, 1,000, or 10,000). To get reasonable temperature increases in 2100, we had to abandon attempts to reproduce clean capital share dynamics from AD-MERGE and instead concentrate just on reproducing the emergence of the clean economy and temperature dynamics, which came at a cost of the carbon-free economy overtaking the carbon-intense by the mid of the 21st century.

To a large extent, this results from the revision in the carbon cycle parameters in DICE2016R (see section 2.1 for detail) which we also implemented in Ada-BaHaMa. According to Rickels et al. (2018), improvement in capturing the long-term dynamics of the carbon cycle in DICE2016R *"comes at the cost of a (too) tight short-term remaining emission budget, limiting the model suitability to analyze low-emission scenarios accurately. With DICE2016R, the compliance with the 2^oC goal is no longer feasible without negative emissions via CDR."*

Given this trade-off between reproducing the clean economy share from AD-MERGE and getting reasonable temperatures, below we consider three options for calibrating the clean economy.

	Option 1	Option 2	Option 3
p_{E1}	0.425	0.425	0.425
p_{E2}	0.6	0.54	0.6
$\phi_{E_1}(0)$	0.3529	0.3529	0.3529
$\phi_{E_2}(0)$	100	100	100
$g\phi_{E_1}(0)$ / $g\phi_{E_2}(0)$	0.1555	0.1555	0.1555
$dg\phi_{E_1}$ / $dg\phi_{E_1}$	0.004	0.004	0.004
Constraint on K2 share	Yes	No	No
Damage function	Calib. to DICE2016R	Calib. to DICE2016R	Old Ada-BaHaMa

Table 2.5: Parameters for several options of the carbon-free economy calibration

In **Option 1**, we reproduce the trajectory of the carbon-free capital in AD-MERGE. As the carbon-free economy, once emerged, quickly skyrockets to almost 100% when unconstrained in Ada-BaHaMa (as shown on the Figure 2.5), we need to add a market penetration constraint to the model to reproduce the AD-MERGE dynamics in Figure 2.4. We attempted to constrain investment in clean capital: $I_2(t) \leq aI_2(t-1)$ where $a \geq 1$, however, the model was infeasible even with $a = 4$. Instead, constraining the share of clean capital in total capital and allowing it to increase no more than 5pp over the 5-year period did the job:

$$K2_{share}(t) \leq K2_{share}(t-1) + 0.05 \tag{2.8}$$

We also increased $\phi_{E_2}(0)$ from 10.43 to 100 (an arbitrary large value) to account for the fact that the advanced clean economy is effectively carbon-free (but we need to keep some emissions for it to be able to calculate production). We tried also higher values of $\phi_{E_2}(0)$ (1,000, 10,000) but they did not improve temperature dynamics as the value of 100 already results in very low emissions from the clean economy.

Even though we succeeded in reproducing the share of clean capital in total capital from AD-MERGE in Ada-BaHaMa (see Option 1 on 2.6), the temperature increase in 2100 was way too high ($+3.4^oC$), and likewise, emissions.

Thus we came up with **Option 2** which reproduces the emergence of the clean economy (in 2030) and reasonably approximates the temperature dynamics in AD-MERGE. In this version, however, clean economy does not unfold little by little, as in AD-MERGE, but jumps very fast to 100% as in our experiments described above.

Option 3 is similar to Option 2 in most parameters, however, it uses an old Ada-BaHaMa damage function which penalizes emissions more heavily than the one calibrated against DICE2016R. Because of this, if we keep price of the clean energy unchanged from Option 2 ($p_{E2} = 0.54$), clean economy starts a decade earlier (in 2020). To shift this to 2030, we apply a higher clean energy price ($p_{E2} = 0.6$). As a result, options 2 and 3 produce almost the same results across most variables, including temperature: $+2.46^oC$ with Ada-BaHaMa vs $+2.51^oC$ with DICE damage function in 2100, which is very close to $+2.46^oC$ in AD-MERGE [2]. However, two versions differ in damages and ELF, and

[2] In DICE and Ada-BaHaMa, temperature increase in measured compared to 1900, while in AD-

somewhat less in emissions.

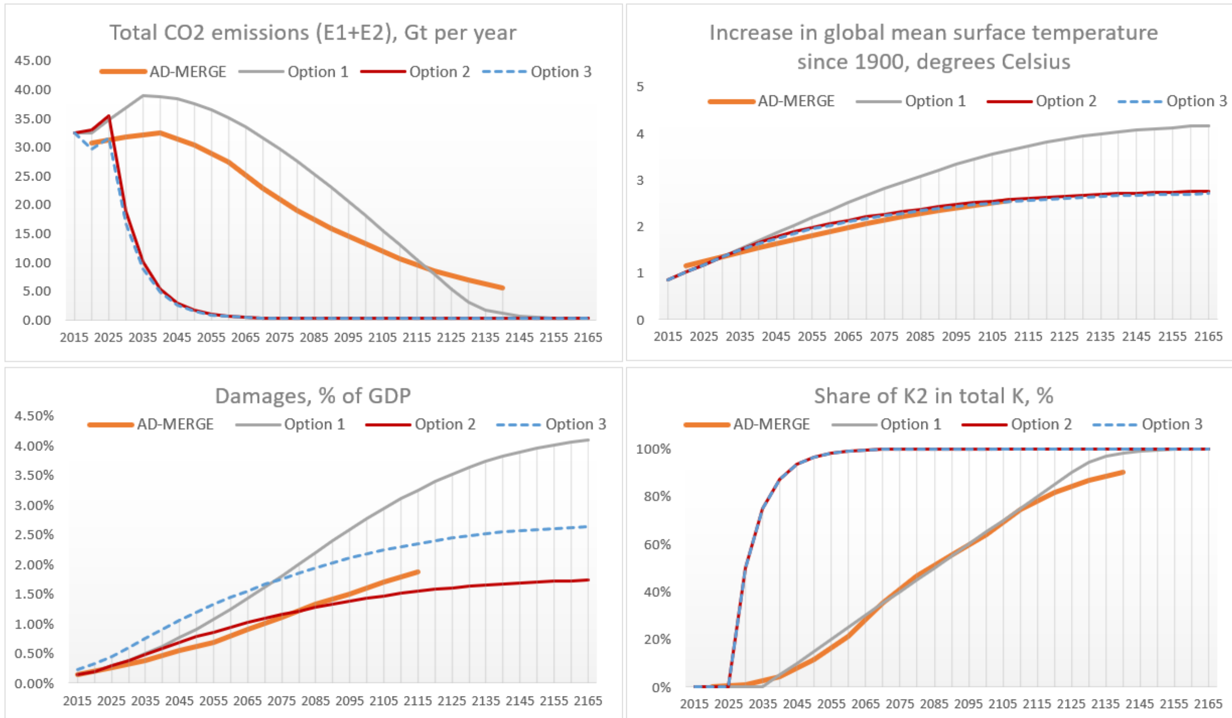

Figure 2.6: Dynamics of main variables in AD-MERGE and Ada-BaHaMa under different calibration options

To explore effects of the new parameterization of the climate module and the carbon cycle, we plugged in emissions and external forcings from Options 1 and 2 into an old Ada-BaHaMa model (with old parameters). As a result, temperature increases in 2105 were much smaller: 2.91^oC (vs 3.4^oC) and 1.87^oC (vs 2.51^oC), for Options 1 and 2, respectively.

Among Options 2 and 3, **we considered Option 2 as a preferable one**. In contrast to Option 3, it produces emissions in 2015-2020 closer to today's values (as measured by IEA) and reproduces damages reasonably close to those in AD-MERGE (though it has less stringent damage function at higher temperatures).

However, once we started experimenting with adding adaptation, CCS and DAC to Ada-BaHaMa, we had to tweak parameters in Option 2 further. Due to the energy price in

MERGE compared to 2000 levels. We add 0.8^oC to AD-MERGE temperature values for comparability.

the advanced clean economy being higher than in the carbon-intense one throughout all modeling horizon, there is an "end-of-period effect" when closer to the end of the adopted horizon the model does not "consider" it is worth keeping a more expensive carbon-free economy and falls back to a carbon-intense one. While in most scenarios this end-of-period effect happens beyond our reporting period, in some others it does kick in within it thus calling for extending the horizon further (and substantially increasing computation time).

To overcome this, we allowed energy price differential between the carbon-intense and the carbon-free economy to change over time. The idea was to let the advanced clean economy to become relatively cheaper in the future due to innovation, learning-by-doing and the economy of scales (which is backed with renewables getting cheaper and cheaper, see, for example, solar photovoltaic panels price in Ritchie and Roser (2014)), while the carbon-intense - to become relatively more expensive as fossil fuel resources exhaust.

We could achieve this effect by gradually increasing the carbon-intense energy prices, by decreasing the carbon-free energy prices, or combining both. Since the carbon-intense economy was calibrated against a counterfactual DICE2016R baseline with the fixed carbon-intense energy prices, we proceeded by decreasing energy prices in the advanced clean economy:

$$p_{E2}(t) = p_{E2} - 0.005t \tag{2.9}$$

where p_{E_2} is the initial price of energy in the advanced clean economy and t is the number of 5-year periods elapsed up to a given moment (1, 2, 3, and so on).

To achieve almost the same dynamics of variables as in Option 2 on Figure 2.6, we had to set $p_{E2} = 0.555$ instead of $p_{E2} = 0.54$. All other parameters were kept unchanged vs Option 2. Also, we had to use $p_{E2}(t)$ instead of p_{E2} in the Equation 1.37. The discrepancies in results between Option 2 and its modification were so minor that we don't add the latter to Figure 2.6 since they will overlay each other.

With these modifications, we effectively allow price in the carbon-free economy to decline about 1% per 5-year period. As a result, energy price in the advanced clean economy becomes equal to that in the carbon-intense economy in 2145 (and goes below it thereafter). Besides, this resolves the "end-of-period effects" mentioned above and allows us to cut the estimation horizon without compromising the desired reporting period thus resulting in faster computation times.

Chapter 3

CCS and DAC modules parameterization

In this chapter, we come up with ranges of parameter values for CCS and DAC modules.

3.1 CCS module parameterization

We need to estimate two parameters in the CCS module (for detail, see section 1.6):

- add-on cost of the CCS, $cost_{ccs}$, in trillion dollars per 1GtCO_2 captured and stored;
- the maximum fraction of emissions from the carbon-intense economy that we can potentially capture, max_{CCS}.

3.1.1 CCS costs

Budinis et al. (2018) conduct a comprehensive review of CCS cost components found in literature - capture, transport and storage costs - and convert them to 2015 US dollars. For capture, they provide CCS costs for different processes which are shown on the left part of Figure 3.1. Using industry CO_2 emission shares as weights (calculated based on IEA (2019) and Ritchie and Roser (2017) data), we take a weighted average of those costs to get a range of min/max levelized capture costs (on the right part of the same Figure). The estimated average capture costs (47-71$) are presented on the last line of Figure 3.1.

Budinis et al. (2018), table 7		
Process plant	**Min**	**Max**
Coal-fired power	41	62
Oxyfuel combustion	45	50
Gas-fired power	52	100
Natural gas combined cycle	75	95
Iron and steel	57	69
Cement production	35	110
Refineries and natural gas processing	20	79

Author's calculations				
Process plant	**Min**	**Median**	**Max**	**Weight (share in 2016 CO_2 emissions)**
Coal-fired electricity	43	50	56	33.2%
Gas-fired electricity	64	81	98	12.3%
Iron and steel	57	63	69	4.7%
Cement production	35	73	110	4.1%
Refineries and natural gas processing	20	50	79	1.5%
CCS, \$/tCO2 captured (weighted average cost)	**47**	**59**	**71**	**55.8%**

Figure 3.1: Cost of captured CO_2 for different process plants (in \$2015/tCO_2)

Budinis et al. (2018) also review transport and storage costs (see Table 3.1 and Table 3.2; average / medium values added by the author of this report[1]). These costs, however, tend to be lower than those adopted in IAMs participating in EMF27. The authors, once again, collected those costs from Koelbl et al. (2014b) and converted them to \$2015 for comparability. While in the literature transport costs vary \$1.3-15.1/tCO_2/250km, the respective range adopted in IAMs is \$0.5-42.5/tCO_2/250km. Storage costs vary \$1.6-22/tCO_2 in the literature compared to \$1-35.1/tCO_2 in IAMs.

Method	Capacity (MtCO_2/yr)	Transportation cost, \$2015/tCO_2/250km	
		Min	Max
Onshore pipeline	3	4.4	11.1
	10	2.2	3.8
	30	1.3	2.2
Offshore pipeline	3	7.3	15.1
	10	3.5	4.9
	30	1.9	2.4

Table 3.1: Transportation costs for CCS (in \$2015/tCO_2). From Budinis et al. (2018), modified from Rubin et al. (2015)

[1]Min/max values are taken from Budinis et al. (2018). Medium values are calculated based on Rubin et al. (2015) 2013 values in EUR by applying the same conversion rates to get costs in \$2015 as for min/max values.

According to an extensive review of 12 IAMs modeling CCS in Koelbl et al. (2014a), most IAMS considered transportation and storage costs in a range of \$US5–300/tCO_2, with all considering these costs closer to the lower bound and only a few studying impacts of the upper bound costs (Bui et al., 2018) and/or assuming that these costs will grow as closer and better storage is used up.

	Min	Medium	Max
Depleted oil and gas field - reusing wells onshore	1.6	4.7	11.0
Depleted oil and gas field - no reusing wells onshore	1.6	6.3	15.7
Saline formations onshore	3.1	7.9	18.8
Depleted oil and gas field - reusing wells offshore	3.1	9.4	14.1
Depleted oil and gas field - no reusing wells offshore	4.7	15.7	22.0
Saline formations offshore	9.4	22.0	31.4
Average	**3.9**	**11.0**	**18.8**

Table 3.2: Cost of CO_2 storage for various storage sites (\$2015/tCO_2). From Budinis et al. (2018) and Rubin et al. (2015)

At the same time, IAMs tend to underestimate investment costs for CCS. According to Budinis et al. (2018), they range 1181–4942 vs. 3552–6816 \$2015/kWe vs in the literature for coal-fired power generation and 856–2394 vs 2313–5088 \$2015/kWe for gas-fired power generation (for detail, see Tables 12 and 14 in the paper). We provide this information for completeness but we do not need it for our modeling.

	Min	Medium/average	Max
Capture	47	59	71
Transport	1	8	15
Storage	2	17	31
Total CCS cost	**50**	**84**	**117**

Table 3.3: Summary of CCS costs (\$2015/tCO_2)

As can be seen above, there is a lot of uncertainty in the estimates of the CCS costs. Table 3.3 summarizes capture, transport and storage costs as found in the literature and presented in the tables above. The last line aggregates all these costs into a single range of values: **\$50-117/tCO_2, or 0.05-0.117 trillion dollars per GtCO_2**, to be in line with

Ada-BaHaMa variable scales. Since it is difficult to come up with a good baseline cost value due to cost uncertainties, we proceed with the sensitivity analysis using values from this range. We also try values beyond this range as costs of energy in Ada-BaHaMa are symbolic and applying real CCS costs along them might not yield a good result.

3.1.2 Share of emissions that CCS can potentially capture

max_{CCS} is the maximum fraction of emissions that can be captured in the carbon-intense economy. To get a value of max_{CCS}, first of all, we need to know the share of emissions coming from stationary sources where CCS technology can be installed. According to IEA (2019) data, electricity and heat production and industry accounted for 61% of CO_2 emissions from the fuel combustion in 2015 (the same value as in 2010 pointing to a stable emissions structure). We get a similar number - 60.5% in 2010 - when making calculations based on the data on GHG emissions from the Fifth Assessment Report by IPCC (Edenhofer et al., 2018)[2]. According to Ritchie and Roser (2017), the share of CO_2 emissions we're interested in ranges from 49% to 67%, depending on whether we also account for manufacturing and construction or consider just electricity/heat production and industry[3]. **So we consider a plausible range for the share of emissions that we can potentially capture with CCS being 49% to 61%, with a midpoint of 55%.**

Secondly, there are limitations to the share of emissions that can be captured at a source. Rubin et al. (2015) present capture rates for five power generation technologies from coal and natural gas which range:

- 86-89% for two post-combustion capture technologies;
- 82-88% for two pre-combustion capture technologies;

[2]IPCC provides all GHG emissions structure in CO_2 equivalent in 2010. If we exclude emissions from agriculture, forestry and land use and assume that CO_2 emissions have a similar structure as total GHG emissions, emissions from electricity and heat production and industry will account for 60.5% of CO_2 emissions.

[3]67% seems a bit high compared to other sources and may point to potential contribution of construction which is not accounted for in other cases.

- 90-98% for an oxy-combustion technology.

This gives us capture rates at a source ranging 82% to 98%, with an average of representative values for five technologies being 88%. Budinis et al. (2018) point out that most CCS studies assume a capture rate of 85–90% for power generation, but higher capture rates (95% and above) may also be achieved at a higher cost.

Multiplying upper and lower bounds for the share of emissions from selected stationary sources with those for capture rates gives us a range of upper limit values for share of emissions that can be captured with today's technologies: $max_{CCS} \in \{40\%, 48\%, 60\%\}$, where $48\% = 55\% * 88\%$ is a multiplication of mid-points of two ranges which we consider our baseline value. We later run a sensitivity analysis for this parameter as well.

3.2 DAC module parameterization

The simplified Approach 2 to DAC modeling that we stick to has three parameters that we need to estimate:

- e_2^{DAC} - emissions from DAC activity, in $GtCO_2$ per each $GtCO_2$ captured and stored
- max_{DAC} - upper limit on the amount of CO_2 that we can capture in a year with DAC
- $cost_{DAC}$ - a lump-sum DAC cost

3.2.1 Emissions from DAC activity

For e_2^{DAC}, we will use emissions by a solid-sorbent system powered by solar energy as described in subsection 1.7. Midpoint emissions of this system equal **0.013 $GtCO_2$ for each $GtCO_2$ captured** (see Figure 1.3). We will not run a sensitivity analysis for this parameter, since the other two parameters will likely have more impact on DAC dynamics.

3.2.2 Upper limit on the amount of CO_2 captured annually

We impose such a limit to prevent the model from producing too much DAC activity over a short period of time which would be unrealistic since DAC is a capital-intense activity and would require time to build the necessary capacities. We did not encounter such an upper limit in the literature, so we try several multiples of 2015 emissions by IEA: 0.5, 1, 2, 3, which roughly amounts to **16, 32.5, 65 and 100GtCO_2 per year.** We will use these capture limits in the sensitivity analysis in the subsequent chapter.

3.2.3 DAC costs

There exist several recent studies estimating DAC cost such as Keith et al. (2018) and Larsen et al. (2019). While both quite agree on the cost ranges for the liquid-solvent technology, the latter also covers solid-sorbent technology as well as several energy price scenarios. Therefore, we choose cost ranges from Larsen et al. (2019). Min and max capture costs in the Table 3.4 reproduce values from Larsen et al. (2019). To get total DAC costs, we add to these costs transportation and storage cost equalling \$18 per tCO_2 (again, using estimates from Larsen et al. (2019)). As we can see, DAC costs decline with more capacities are built. We also calculate midpoints of cost ranges which we will use in a sensitivity analysis: **123, 149, 191, and 243 dollars per tCO_2**[4]. To explore the impact of very optimistic DAC costs, we also include a value of **\$64/tCO_2** to the list (the minimum total cost in the Table 3.4).

	Capture costs			**Capture + transport and storage**		
	Min	Midpoint	Max	Min	**Midpoint**	Max
First Mt capacity	124	225	325	142	**243**	343
7-9mn tCO_2	85	173	261	103	**191**	279
76-136mn tCO_2	58	131	204	76	**149**	222
856-2258mn tCO_2	46	105	164	**64**	**123**	182

Table 3.4: DAC costs (in \$/tCO_2), according to Larsen et al. (2019)

[4]When converted to Ada-BaHaMa units, these costs amount 0.123, 0.149, 0.191, and 0.243 trillion dollars per GtCO_2.

Chapter 4

Experimental results

4.1 Sensitivity analysis for CCS parameters

We run sensitivity analysis using the following parameter values:

- CCS cost: 0.04, 0.05, 0.084 and 0.117 trillion dollars per $GtCO_2$, **or \$40, \$50, \$84 and \$117 per tCO_2 captured and stored**[1]. We add a cost of \$40 to the list of costs defined in section 3.1 since higher cost values - \$84 and \$117 - seem to be prohibitive and result in almost no CCS activity.

- The maximum share of emissions in the carbon-intense economy that we can capture max_{CCS}: **40%, 48% and 60%** (see section 3.1).

Figure 4.1 shows CCS volumes under different combinations of these values. Lines of the same color refer to the same cost value. Under the highest CCS cost (\$117), CCS deployment does not exceed $0.1GtCO_2$ at most, therefore, we do not show the results for this cost value on the plot. Even under the second-highest cost (\$84), CCS volumes are negligible.

There are several conclusions that we can make right away from this plot. First, CCS is (almost) not deployed when cost is prohibitive (\$84-117, in our case). Second, CCS

[1]Though we use costs in trillion dollars per $GtCO_2$ in the model, in this description, we use costs in $\$/tCO_2$ for easier interpretation.

cost impacts when CCS starts to be deployed, with smaller costs shifting the start earlier. Third, the maximum share of emissions we can capture "decides" how much we capture and for how long, the higher values leading to increased CCS deployment.

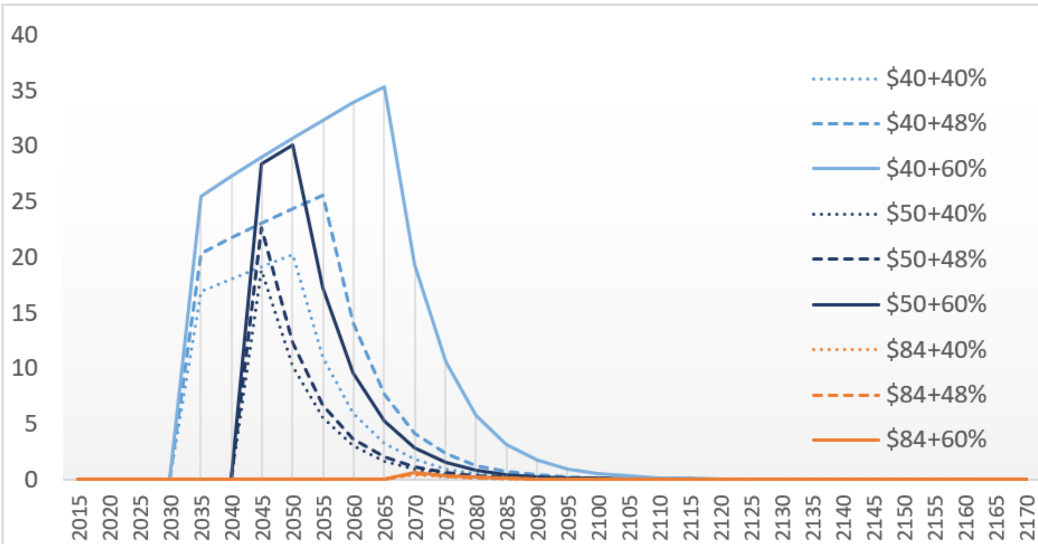

Figure 4.1: CCS deployment, in $GtCO_2$ captured and stored, under different CCS costs and capture limits

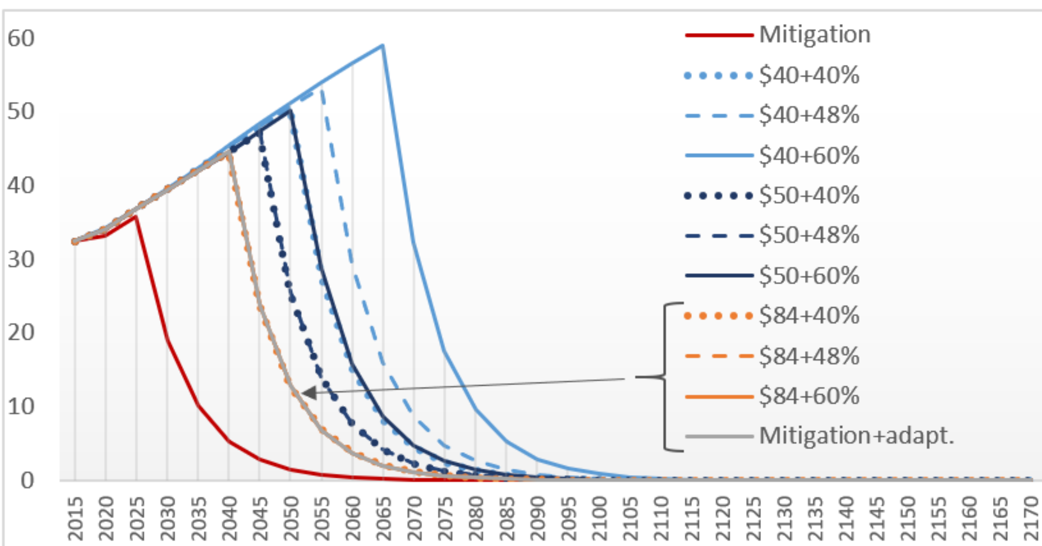

Figure 4.2: CO_2 emissions (in Gt) from the carbon-intense economy (E1) before capture under different CCS costs and capture limits

Next, we can explore how changing CCS parameter values impacts emissions from the carbon-intense economy (see Figure 4.2; emissions before capture are shown). Compared to the mitigation only (carbon-intense/carbon-free economy and no adaptation/CCS), the best combination of CCS parameters (cost of \$40 and capture share of 60%) results in growing CO_2 emissions up to 2065. At the same time, costs of \$84 and \$117 (the latter not shown on the plot) almost don't impact emissions which continue to grow until 2045, just as they would in a scenario with mitigation and adaptation, but no CCS.

Emissions dynamics is heavily related to the deployment of the carbon-free economy (see Figure 4.3). We don't show results for costs of \$84 and \$117/tCO_2 since they effectively coincide with those of mitigation with adaptation. Depending on parameter values in the CCS module, the start of the carbon-free economy can be delayed, and the more so the more optimistic assumptions regarding CCS cost and potential capture share we make. However, the carbon-free economy appears, sooner or later, under all explored values of CCS-related parameters.

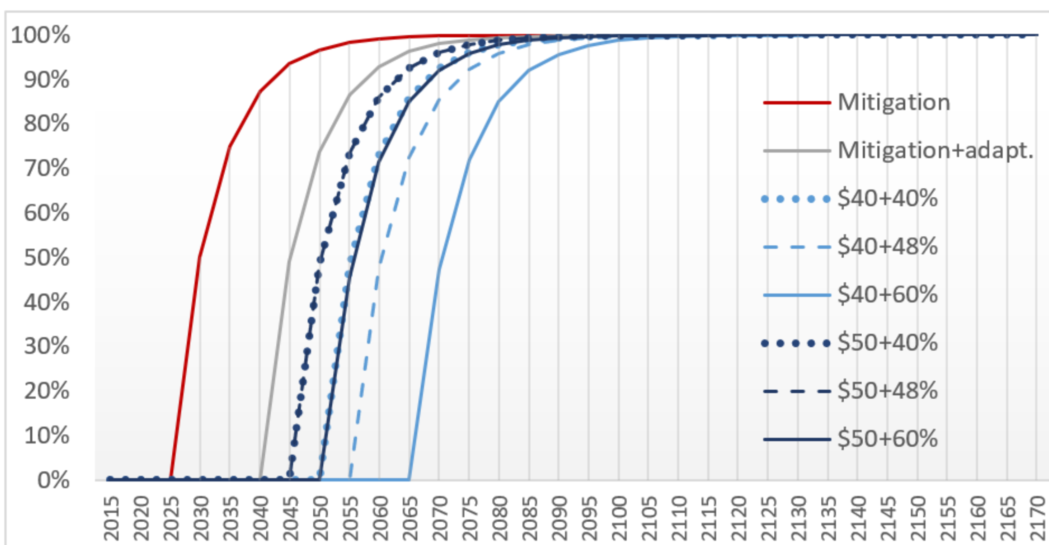

Figure 4.3: Share of capital in the carbon-free economy in total productive capital under different CCS costs and capture limits

With regard to the atmospheric temperature increase vs pre-industrial level, all combinations of CCS parameters tested yield quite uniform results which are close to those of mitigation with adaptation (see Figure 4.4). If we zoom in the plot, we will see that the most optimistic CCS option (\$40 + 60%) results in the highest temperatures by 2170 while producing the lowest temperatures around mid-21st century. This happens because this option results in smaller cumulative emissions by 20150 but higher ones (1,708 $GtCO_2$) by 2170 than other options (1,571 $GtCO_2$, on average) due to the latest emergence of the advanced clean economy.

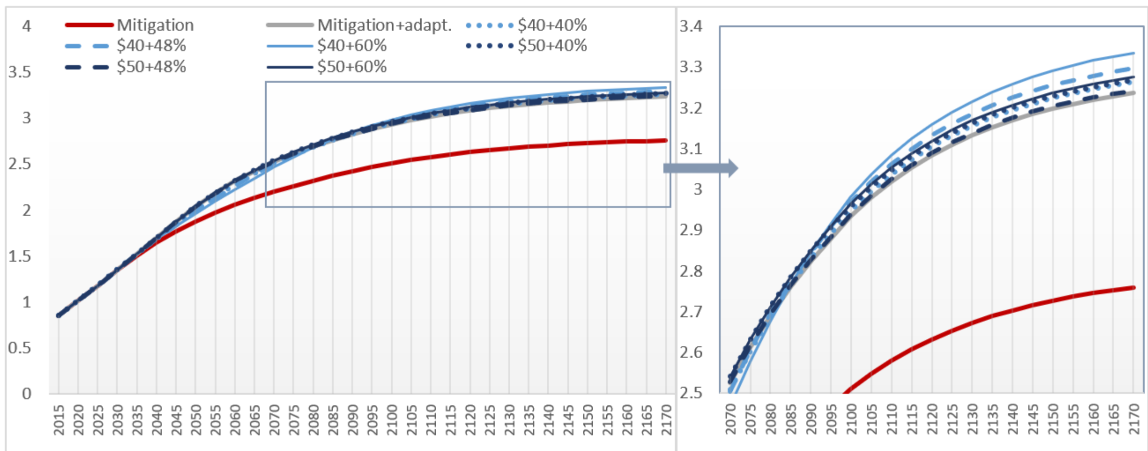

Figure 4.4: Atmospheric temperature increase vs 1900 under different CCS costs and capture limits

Cumulative CCS volumes over the next 150 years vary 207 to 1,284 $GtCO_2$ for CCS costs of \$40 and \$50 and are at most 7.4Gt for higher costs (see Figure 4.5). This is within the cheapest range of storage costs as shown on Figure 1.1, so we don't need to impose a constraint on cumulative CCS volumes, following the discussion in section 1.6.

	Maximum capture fraction		
CCS cost	**40%**	**48%**	**60%**
$40	492	730	1,284
$50	207	249	484
$84	5	6	7
$117	1	1	1

Figure 4.5: Cumulative CCS deployment by 2170, in $GtCO_2$ captured and stored, under different CCS costs and capture limits

4.2 Sensitivity analysis for DAC parameters

In this section, we conduct sensitivity analysis to changes in DAC module parameters and explore effects of applying the following parameter values (see section 3.2 for details):

- DAC cost: **\$64, \$123, \$149, \$191, and \$243/tCO_2** captured and stored with DAC
- The maximum volume of CO_2 that we can capture with DAC technology per year max_{DAC}: **16, 32.5, 65 and 100Gt**.

First of all, we run this analysis in the setting with mitigation (carbon-free economy), adaptation and DAC (but no CCS). Secondly, we repeat the same analysis, including CCS with an optimistic cost of capture and storage (\$40/tCO_2) and a baseline value for the share of emissions we can capture (48%).

4.2.1 Sensitivity analysis: no CCS in the mix

DAC deployment depends heavily on the DAC cost. When DAC is cheaper, it is deployed earlier. When DAC costs \$243/tCO_2, it does not appear during our modeling horizon (up to 2215), therefore, this cost is not reported on the outputs below. Roughly doubling the cost shifts DAC emergence by 30-40 later, depending on the capture limit used (see Figure 4.6). The capture limit also shifts the moment when DAC comes into play, but to a much smaller extent. For most combinations of DAC costs and capture limits, doubling the latter shifts DAC emergence by 5 years forward (range: 0-10 years).

	DAC capture limit, GtCO_2/year			
DAC cost, \$/tCO_2	**16**	**32.5**	**65**	**100**
64	2055	2060	2065	2070
123	2095	2095	2105	2110
149	2105	2110	2115	2120
191	2135	2135	2135	2140

Figure 4.6: A year when DAC starts being deployed, under different DAC costs and capture limits

The imposed DAC capture limit is a binding constraint that stays active for all combinations of parameters tried. If it were not used, DAC would appear later, for a shorter duration, and in higher volumes per period (often exceeding 400GtCO_2 per year at some point). As a result, such a constraint spreads out DAC activity more uniformly in time - and the more so, the lower the carbon dioxide capture limit (see Figure 4.7). For example, under the cost of \$123/tCO_2 and the limit of 16GtCO_2, DAC is deployed during 2095-2180, while under the limit of 100GtCO_2 - only during 2110-2145.

When DAC is cheaper, not only it starts earlier, but is also deployed longer. Under the highest cost that still results in some DAC activity (\$191/tCO_2), DAC deployment is squeezed into 15-25 years around mid-22nd century, while under the cheapest cost (\$64/tCO_2) - is spanning across 70-145 years depending on the capture limit. Overall, in our model, DAC is used as an on-demand technology that is being phased out once the desirable climate effects have been reached.

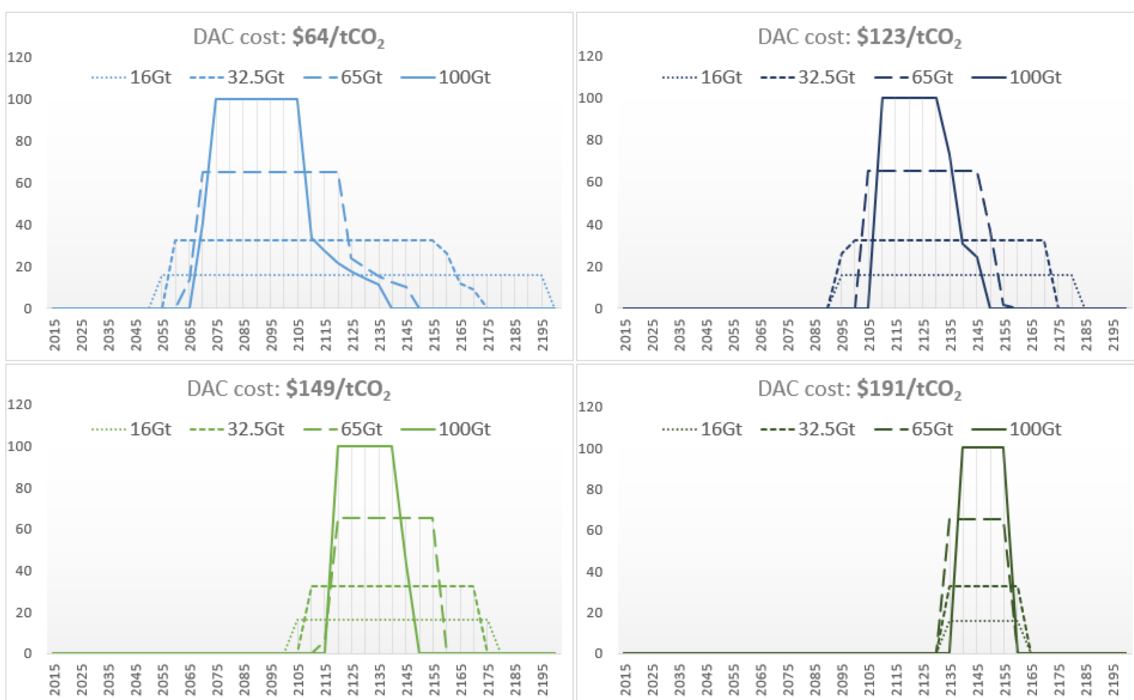

Figure 4.7: DAC deployment, in GtCO_2 captured and stored, under different DAC costs and capture limits

More stringent capture constraints not only call for a longer application of DAC to reach desired climate effects, but also result in smaller cumulative DAC deployment (see Figure 4.8). The most pronounced effect is for 16 $GtCO_2$/year limit. If we decrease the limit twice from 65 to 32.5/$GtCO_2$ per year, the model will partially compensate for this by spreading DAC activity longer, and the cumulative volumes captured will decline 23%, on average (14-40%). For the 16/$GtCO_2$ per year limit the cumulative captured volumes are twice as low as for 32.5/$GtCO_2$ limit, just as the limit itself is.

Cumulative DAC deployment ($GtCO_2$) by 2170

	DAC upper limit, $GtCO_2$/year			
DAC cost, $/$tCO_2$	16	32.5	65	100
$64	1,920	3,485	4,045	4,329
$123	1,280	2,568	3,116	3,139
$149	1,120	2,113	2,630	2,717
$191	480	975	1,625	2,000

Figure 4.8: Cumulative DAC deployment by 2170, in $GtCO_2$ captured and stored, under different DAC costs and capture limits

	DAC capture limit, $GtCO_2$/year			
DAC cost, $/$tCO_2$	16	32.5	65	100
64	2045	2050	2060	2065
123	2045	2045	2050	2050
149	2045	2045	2045	2045
191	2045	2045	2045	2045

Figure 4.9: A year when the advanced clean economy emerges, under different DAC costs and capture limits

DAC deployment can impact the moment when carbon-free economy emerges. In a model with mitigation and adaptation only, the carbon-free economy emerges in 2045 (delayed by 15 years due to adaptation vs a situation with no adaptation). Under some combinations of the tested DAC parameters, the start of the advanced clean economy may shift even further. For example, a very optimistic DAC scenario with a cost of \$64/tCO_2 captured and stored and a capture limit of 100$GtCO_2$/year can delay the start of the carbon-free economy to as far as 2065 (see Figure 4.9). At the same time, under higher DAC costs (\$149-191), the advanced clean economy emerges in 2045, no matter what capture limit, just as it would without DAC.

Emergence of the carbon-free economy is negatively correlated with the emissions from the carbon-intense economy. Under the most optimistic DAC scenario (cost of \$64 + 100Gt limit), the carbon-intense economy and its emissions continue growing until 2060 - for 20 years longer than in case of mitigation+adaptation only. For higher costs (\$149-191), emissions dynamics almost don't differ from mitigation+adaptation only.

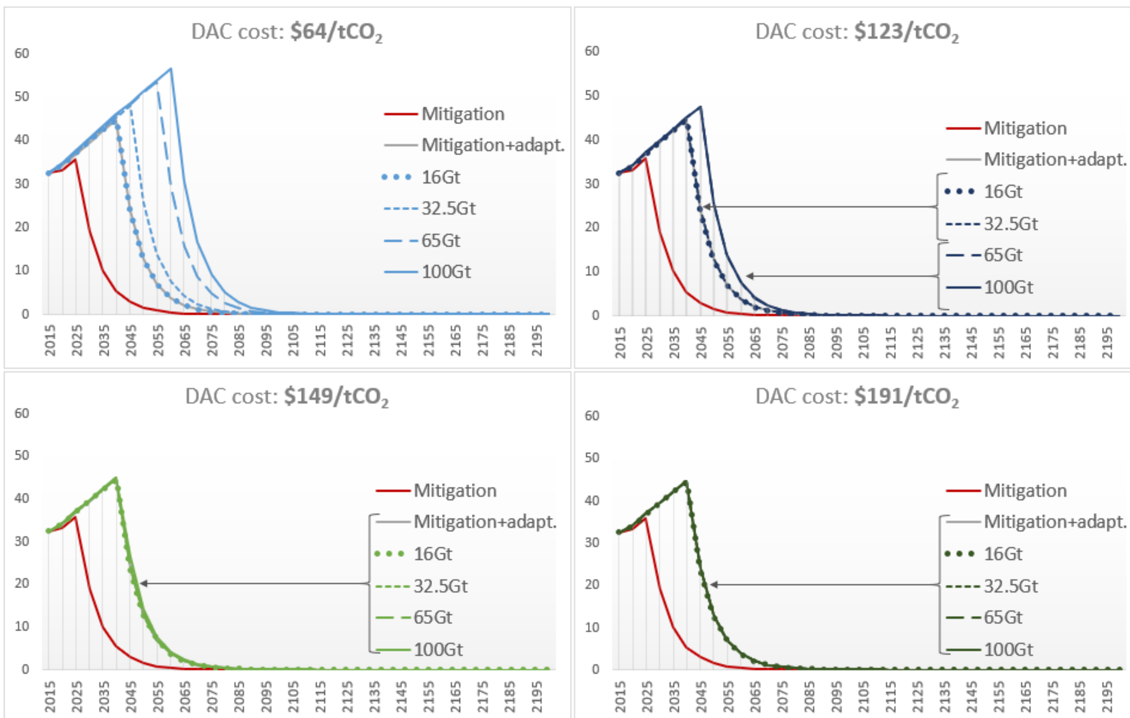

Figure 4.10: CO_2 emissions from the carbon-intense economy (in Gt), under different DAC costs and capture limits

Temperature dynamics is directly related to the amount of CO_2 captured with DAC. The smaller the price, the higher the capture limit and the higher the amount captured, the more drastic climate results we can achieve (see Figure 4.11). Under the cheapest DAC (\$64) and capture limits of 32.5GtCO_2/year and higher, the decarbonization of the atmosphere is so pronounced that by 2175 temperature returns to the current levels (0.85^oC)

or goes down even further - to 0.6^oC increase vs pre-industrial level. Under the most expensive DAC scenario ($191), on the other hand, we can hardly return to 2^oC by this time even with the highest capture limit of 100GtCO_2/year.

One more takeaway from this plot is that when DAC is cheaper ($64-123) and the capture limits are more generous, the temperature can exceed the "mitigation+adaptation" levels before going down. When DAC is more expensive ($149-191), the temperature dynamics does not differ from the scenario with mitigation+adaptation only until the moment of DAC deployment.

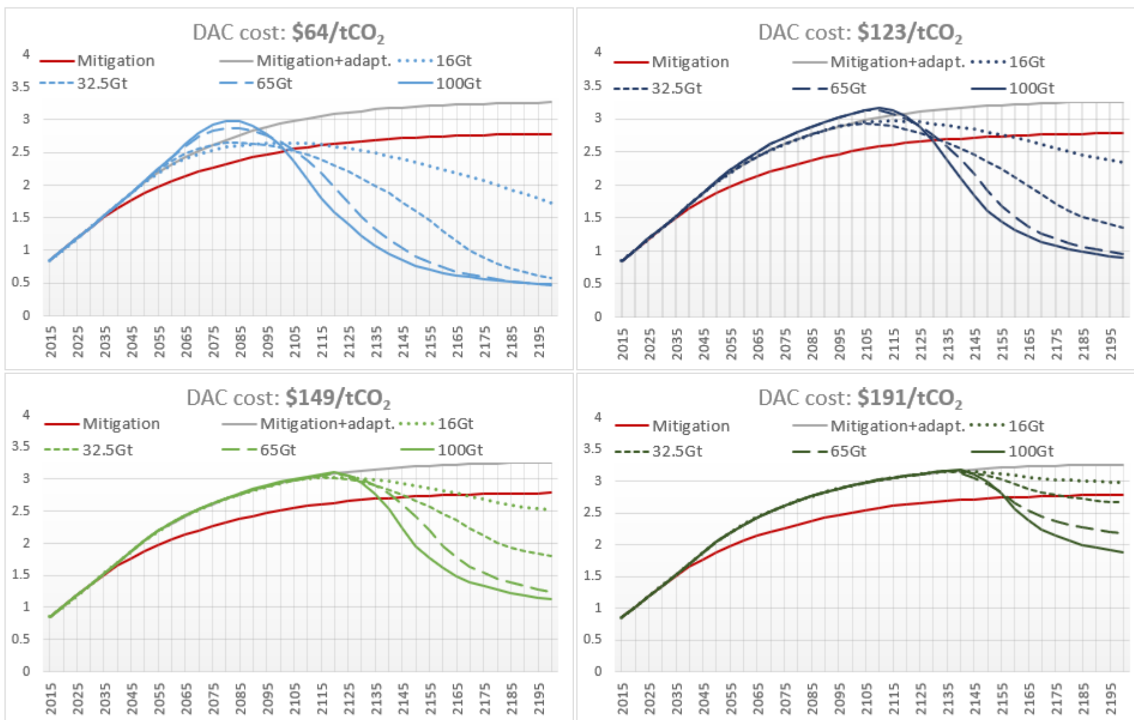

Figure 4.11: Atmospheric temperature increase vs 1900, under different DAC costs and capture limits

4.2.2 Sensitivity analysis: adding CCS to the mix

In this section, we briefly explore how adding CCS to the model with mitigation, adaptation and DAC impacts dynamics of important variables. We discuss only those variables whose dynamics visibly changed after including CCS to the model.

With CCS added to the model, time when DAC starts being deployed (see Figure 4.6) stays the same for all DAC parameter combinations except for cost of \$191 and a limit of 16GtCO_2/year, when it shifts 5 years earlier. Also, the dynamics of volumes captured with DAC are quite similar to those depicted on Figure 4.7, therefore, we do not show them here. Overall, the cumulative volume of CO_2 captured with DAC tends to be a little higher when CCS is available vs a setting with no CCS (see Figure 4.12; note that dotted lines repeat values from Figure 4.8).

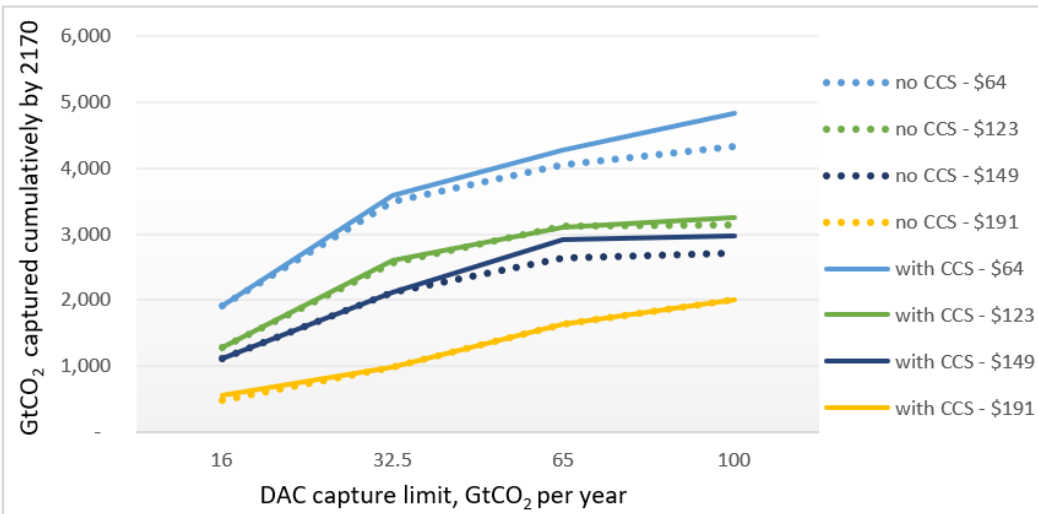

Figure 4.12: Comparison of cumulative DAC deployment by 2170, in GtCO_2 captured and stored, with and without CCS availability

	DAC capture limit, $GtCO_2$/year			
DAC cost, \$/tCO_2	16	32.5	65	100
64	2065	2070	2085	2100
123	2060	2065	2065	2070
149	2060	2060	2065	2065
191	2060	2060	2060	2060

Figure 4.13: A year when the advanced clean economy emerges, under different DAC costs and capture limits and CCS in the mix

Adding CCS to the mix, however, significantly shifts the emergence of the advanced clean economy: by 15-20 years under most parameter combinations, but for the cheapest

DAC ($64) and high capture limits (65-100GtCO_2/year) transition to the advanced clean economy may get delayed by 25-35 years vs a setting without CCS. Overall, that means that under the promise of cheap enough CCS and DAC, we might not need to transition to the clean economy almost until the end of the 21st century.

Along with the shift in the carbon-free economy deployment, there is a change in dynamics of emissions from the carbon-intense economy. With "optimistic" CCS added to the model, emissions start to decline at least 15 years later than they would without it, in some cases growing even until the end of the current century.

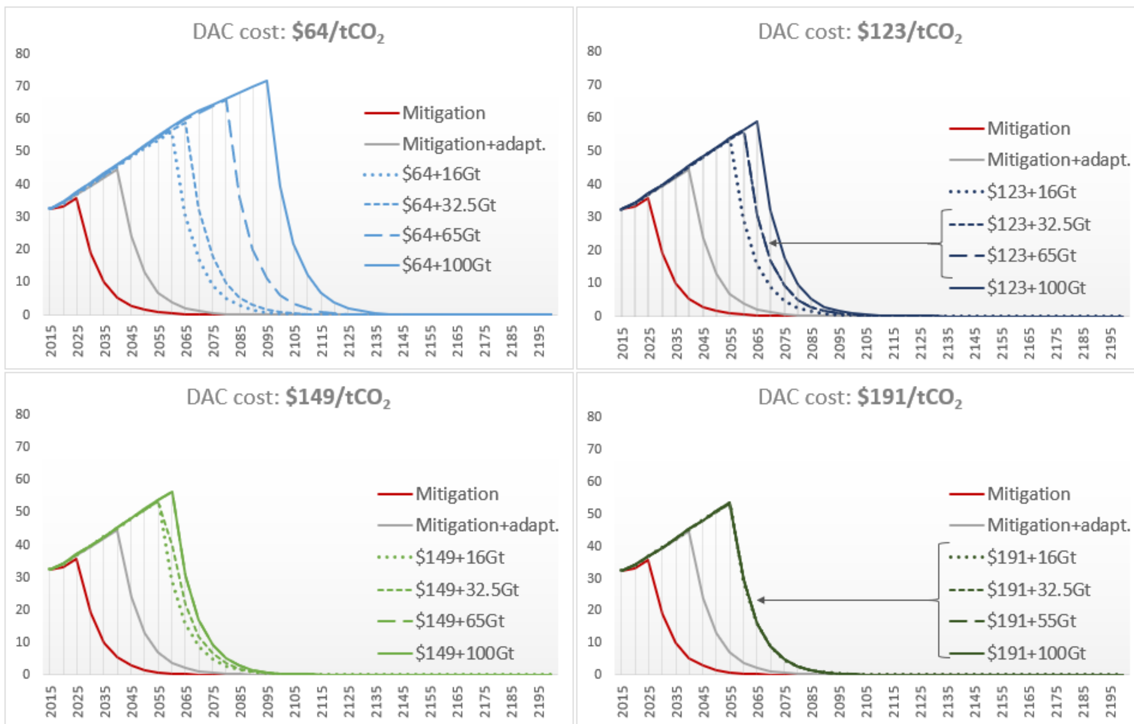

Figure 4.14: CO_2 emissions from the carbon-intense economy (in Gt), under different DAC costs and capture limits

Temperature dynamics are quite similar in settings with and without CCS and yield basically the same conclusions. In fact, differences in trajectories caused by variation of DAC parameters are much more pronounced than when adding CCS to the model. For this reason, we do not provide updated temperature plots here.

4.3 Exploring interplay of climate policy options

In this section, we explore how available mitigation, adaptation and geoengineering options impact dynamics of main economic and climate indicators. We consider the following combinations of policy options:

1. A mitigation setting where we have only carbon-intense and carbon free economies, and no adaptation, CCS or DAC: **Miti**.

2. Mitigation with proactive and reactive adaptation: **Ada**.

3. Mitigation, proactive and reactive adaptation and CCS: **Ada-CCS**.

4. Mitigation, proactive and reactive adaptation and DAC: **Ada-DAC**.

5. Mitigation, proactive and reactive adaptation, CCS and DAC: **Ada-CCS-DAC**.

In scenarios with CCS, we assume the maximum share of emissions from the carbon-intense economy we can capture to be 48%, which is a realistic value of this parameter given the current emissions structure and CCS capture rates. We also assume optimistic CCS cost of \$40/tCO_2 captured and stored which is below the lower bound of the cost range estimated in section 3.1 (\$50-117/tCO_2). We select this combination of CCS parameters since it results in 730GtCO_2 captured with CCS over the 21st century - a value that is within the range produced by other IAMs as analyzed in Koelbl et al. (2014a) though closer to its lower bound: 600–3,050 GtCO_2. Under the CCS cost of \$50, we don't reach 500GtCO_2 (see Figure 4.5), however, this a cost worth considering in the future research.

In settings that include DAC, we assume DAC cost of \$123/tCO_2 which is the mid-point cost of capture and storage when DAC is deployed at the gigaton scale (as estimated by Larsen et al. (2019)). We also assume that the maximum amount of carbon dioxide that we can capture in a year equals 2015 emissions from fuel combustion - about 32.5GtCO_2 according to IEA (2019). We stick to this value since it is large enough to allow deploying vast DAC capacities but not too large to lead to steep decarbonization of the atmosphere that might itself be risky.

Compared to the mitigation only, an opportunity to compensate part of the damages from the climate change with adaptation leads to longer development of the carbon-intense economy, and carbon-free economy comes into play 15 years later than in case of mitigation only (2045 vs 2030). The same happens if we add DAC to the mix when CCS is not available. Adding CCS to the mitigation options shifts the emergence of the advanced clean economy another 15 years further - to 2060, and deploying all possible options (Ada-CCS-DAC) - to 2065 (see K1 and K2 dynamics on Figure 4.15[2]).

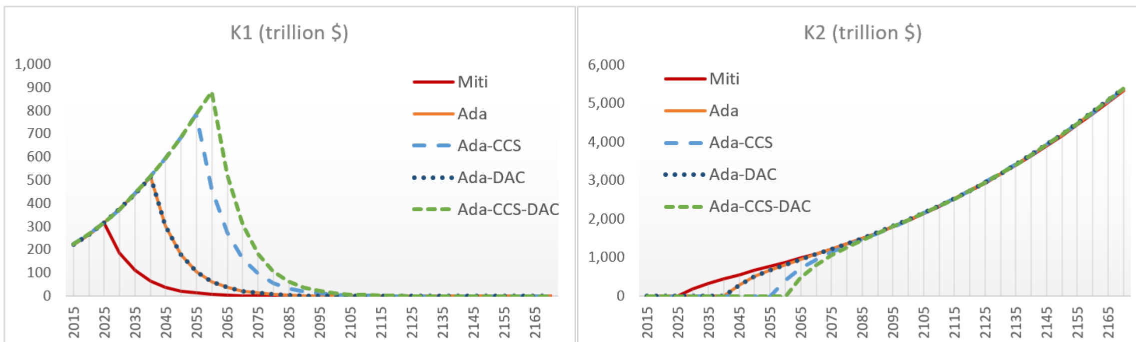

Figure 4.15: Productive capital accumulation in the carbon-intense (K1) and carbon-free (K2) economy, trillion dollars

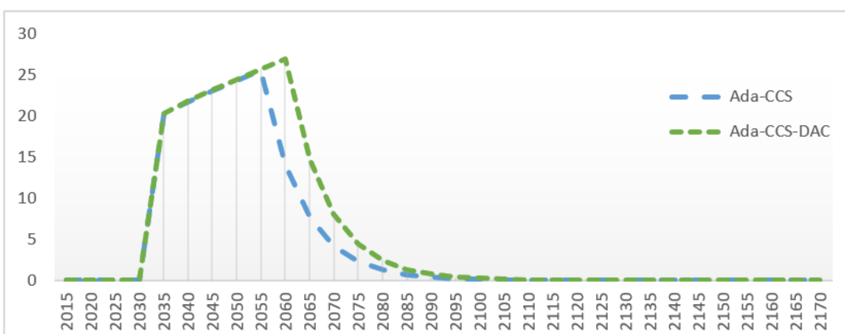

Figure 4.16: CO_2 volumes captured and stored with CCS, in Gt

If CCS is available, it gets deployed before the advanced clean economy, pushing the latter further in time and acting as a "bridge technology". CCS deployment starts in 2035

[2]Note that in the updated Ada-BaHaMa, productive capital is accumulating much faster than in the previous versions. This is due to its calibration according to the DICE2016R.

and grows until 2055 (without DAC) or until 2060 (with DAC) before tapering off due to the advanced clean economy coming into play (see Figure 4.16). It is interesting to note that DAC prolongs CCS deployment and shifts the carbon-free economy emergence without being actually deployed itself until late in the 21st century (see Figure 4.17). It looks like even the promise of DAC cheap enough could delay the transition to the advanced clean economy.

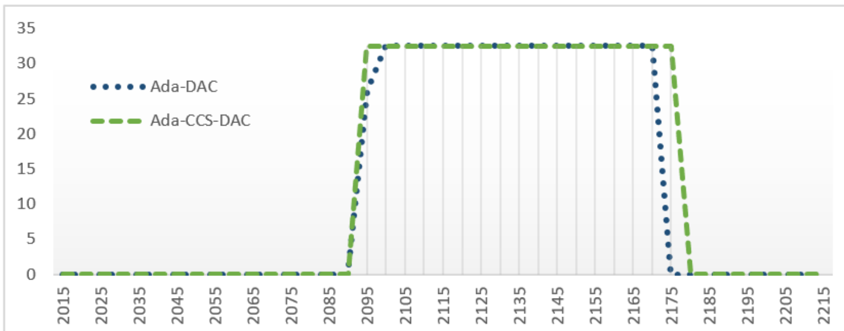

Figure 4.17: CO_2 volumes captured and stored with DAC, in Gt

Adaptation deployment depends on a policy mix considered. When DAC is not available, adaptation progressively grows with temperatures and damages. When DAC is deployed in 2095, proactive adaptation capital accumulation and reactive adaptation spending grow a decade more, peak in 2205 and then taper off. CCS deployment results in somewhat higher adaptation than in "no-CCS" scenarios due to the fact that it postpones transition to the advanced clean economy.

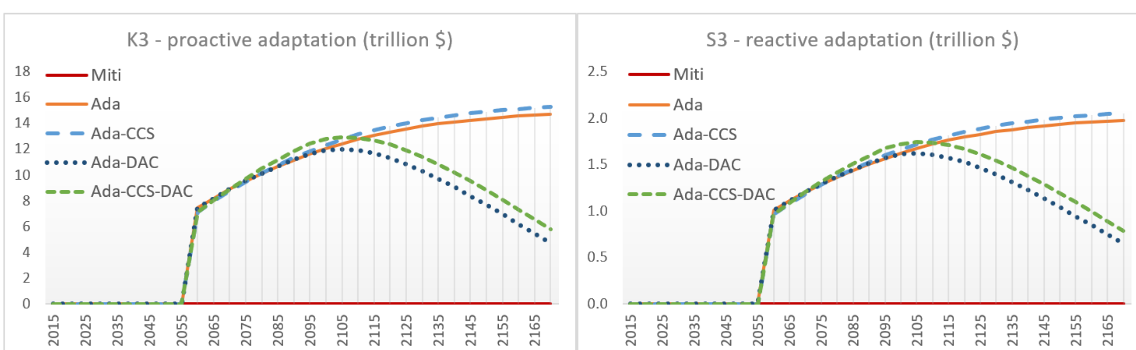

Figure 4.18: Adaptation capital (K3) and spending (S3), trillion dollars

Full mixture of policy options including DAC and CCS preserves the carbon-intense economy the longest and leads to the highest emissions produced in this economy prior to capture with CCS (see right pane on Figure 4.19). When we subtract emissions captured and stored with CCS, emissions entering the atmosphere decrease (see left pane on Figure 4.19). A sawtooth pattern in total emissions when CCS is deployed is due to the fact that CCS prolongs the carbon-intense economy while not being capture more than a given fraction of its emissions.

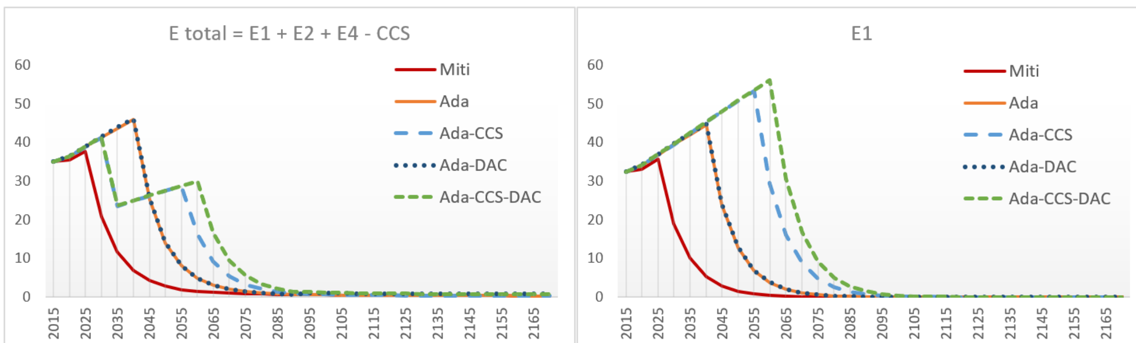

Figure 4.19: Total CO_2 emissions to the atmosphere (left pane) and emissions produced by the carbon-intense economy before capture with CCS (right pane), in $GtCO_2$

However, scenarios with CCS result in higher cumulative emissions to the atmosphere than similar scenarios without CCS, which explains higher deployment of adaptation alongside CCS (see Figure 4.20; note that here we show emissions that enter the atmosphere and could still be captured by DAC later).

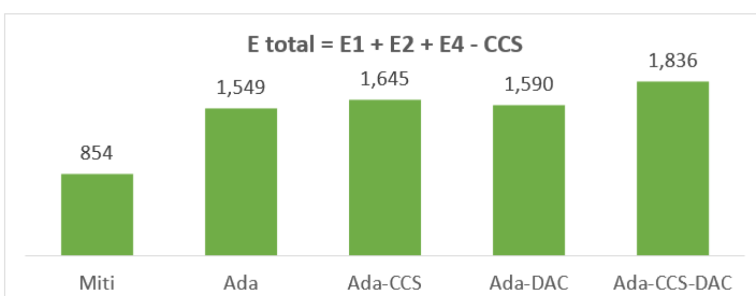

Figure 4.20: Cumulative CO_2 emissions to the atmosphere by 2170, in $GtCO_2$

Compared to the mitigation only, all other scenarios result in higher temperatures by end-21st century (2.5^oC vs around 3^oC, see Figure 4.21). To a much extent, this is due to effective adaptation. It should be noted that the current version of Ada-BaHaMa produces a higher temperature difference in 2100 between mitigation and mitigation+adaptation (about 0.5^oC) than, for example, a version described in Bahn et al. (2012) or in Bahn et al. (2015) (about 0.2^oC).

Scenarios with CCS having higher cumulative emissions than those without CCS result in somewhat higher temperatures. In its turn, DAC effectively removes CO_2 from the atmosphere, resulting in temperatures in 2170 by about 1^oC lower than those at a peak.

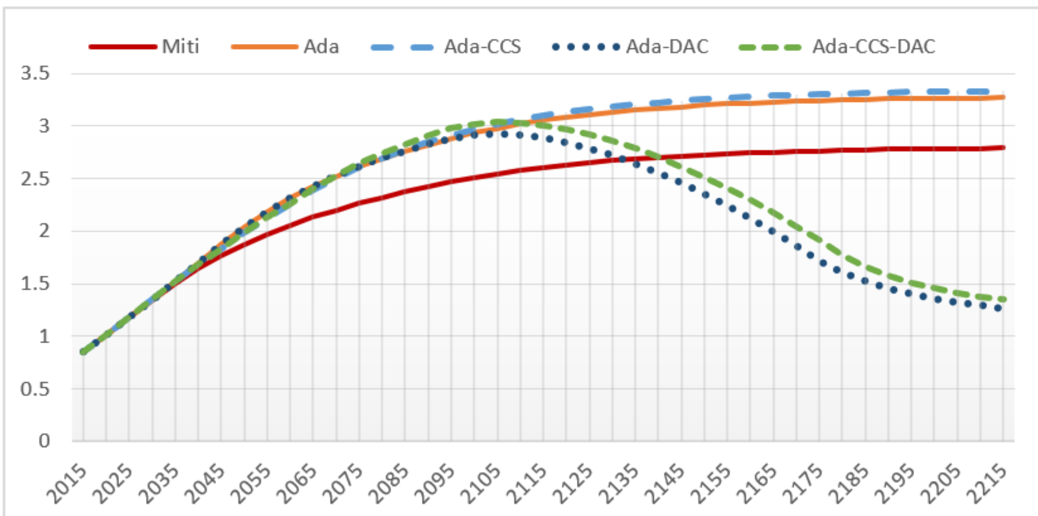

Figure 4.21: Atmospheric temperature increase vs 1900, degrees Celsius

Conclusion

In this project, we've updated Ada-BaHaMa according to the latest changes in DICE2016R, re-calibrated and augmented it with CCS and DAC, conducted a sensitivity analysis and explored an interplay between different climate policy options.

With regard to Ada-BaHaMa calibration, we successfully re-calibrated the counterfactual baseline (that does not account for damages from the climate change) so that it matches very well a similar scenario in DICE2016R. However, re-calibrating the carbon-free economy was not an easy task in a simple model which Ada-BaHaMa is. Despite many attempts, we had to accept a compromise calibration that reproduces the debut of the carbon-free economy in AD-MERGE (but not its dynamics) and reasonably well approximates its temperature and damages trajectories.

We modeled CCS with a levelized cost per unit of CO_2 captured. We considered modeling DAC through its capacity accumulation, but due to time constraints and difficulties in implementation, we modeled it by using levelized technology costs as well. In both cases, we explored costs available in the literature, and due to uncertainties in cost estimates for both technologies proceeded with a sensitivity analysis.

Despite our simplistic approach to modeling CCS and DAC, we nonetheless could make some important conclusions:

- No matter what parameters we tried, the transition to the advanced clean economy happened in all cases, albeit postponed by up to 70 years (to 2100) in scenarios with the most optimistic assumptions for CCS and DAC.

- When deployed on a non-negligible scale, CCS comes before the carbon-free economy, pushing its emergence further in time. By delaying transition to the clean economy, it results in somewhat higher cumulative CO_2 emissions and higher temperatures than similar scenarios without CCS.

- The smaller CCS cost, the earlier it is deployed and for a longer time. CCS costs of \$84-117/tCO_2 are prohibitive in Ada-BaHaMa. CCS capture limit is another important factor of CCS adoption and the higher it is, the more CO_2 is captured and the longer technology is deployed under the same cost.

- Similarly, when DAC is cheaper, not only it starts earlier, but is also deployed longer and with higher cumulative capture. Doubling DAC cost shifts DAC emergence by 30-40 years forward, while doubling the capture - by 5 years in most cases. More stringent capture constraints not only spread DAC deployment over a longer time, but also result in smaller cumulative DAC activity.

- More optimistic DAC assumptions may delay transition to the clean economy. Availability of DAC prolongs CCS deployment and shifts the carbon-free economy emergence without DAC being deployed itself until late in the 21st (or even in the 22nd) century. It looks like even the promise of DAC cheap enough could delay the transition to the carbon-free economy.

- In all scenarios, DAC leads to decrease in atmospheric temperatures, however, its climate impact heavily depends on the underlying assumptions. Depending on the parameter combinations tried, temperatures in 2170 span $0.5-3^{o}C$.

We realise that we used a simplistic approach to modeling CCS and DAC which could be improved in the future research. Under the current approach, we could consider using more elaborate cost functions for CCS and DAC that would respond to technology developments and/or storage limitations. Also, we could try accounting for potential outgassing of CO_2 from the storage. We might also consider modeling DAC with a production function as offered in Bahn and Haurie (2020). We could also revisit the damage function and/or adaptation to make a feedback from the climate change stronger.

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Appendix A – Calibration in section 2.4

Here, we provide a step-by-step process of calibrating Ada-BaHaMa against a counterfactual baseline as described in section 2.4. Though we finally don't make use of this calibration, it is provided for completeness:

1. Fix A_0, gA_0 and dgA at the levels obtained in the section 2.2 (see Table 2.2).

2. Fix energy prices per unit of emissions at the same levels as in the initial Ada-BaHaMa model we started working with (Bahn et al., 2015): $p_{E1} = 0.425$ and $p_{E2} = 0.55$.

3. Assume that the share of capital in low-carbon economy at the initial time point equals the share of low-carbon energy in total primary energy supply (18.5%) and fix $K_1(0)$ and $K_2(0)$ accordingly throughout the calibration. We assume the same shares for labour ($L_1(0)$ and $L_2(0)$) but do not fix them in t_0. The model tends to produce almost the same shares of low-carbon component in capital, labour and total production, so it's enough to fix just capital shares. However, the assumption about labour shares will come in handy later.

4. Using 2015 IEA data on primary energy supply and CO_2 emissions from combustion (IEA, 2019) from different energy sources, we calculated that, on average, all low-carbon energy sources produced 29.56 times less CO_2 per unit of energy than carbon-intense sources. We thus assumed the following relationship between the energy efficiency of two economies at the initial time point:

$$\phi_{E_2}(0) = 29.56\phi_{E_1}(0) \tag{1}$$

5. Using the same IEA data, we calculated the share of emissions from low-carbon economy in total industrial emissions in 2015: 0.76%. Given $E(0) = 36.846$ in DICE2016R counter-factual baseline, we found $E_1(0) = 36.565$ and $E_2(0) = 0.281$ and set those values as targets for the calibration.

6. We move on to finding the best initial energy efficiency of emissions, $\phi_{E_1}(0)$ and $\phi_{E_2}(0)$, to match the target levels of emissions calculated at the previous step. We start with $\phi_{E_1}(0) = 0.3529$ (a parameter from Table 2.2) and $\phi_{E_2}(0) = 29.56\phi_{E_1}(0) = 10.43$. These parameters are apparently too high and will lead to lower emissions than needed, which we verify in GAMS. So we decrease them while keeping the proportion from the equation 1. If we still undershoot the target emissions, we need to decrease the parameters further. If we overshoot the target emissions now, we pick parameter values in between the initial ones and the tried ones. Using this approach, we can quite fast narrow down our search.

   To keep track of our changes, we collect in a spreadsheet $E_1(0)$ and $E_2(0)$ from the GAMS output for each $\phi_{E_1}(0)$ and $\phi_{E_2}(0)$ we try. For each pair of parameter values, we get total emissions $(E_1(0) + E_2(0)$ and can estimate how much we deviate from the target emissions. After a few runs with changing parameters, if we still fail to reasonably match the target emissions, we can make a scatter plot in Excel with total emissions on X axis versus $\phi_{E_1}(0)$ on Y axis (we can take only $\phi_{E_1}(0)$ since it's carbon-intense economy that produces almost all emissions). Adding a trend line on a scatter plot in Excel, we can get a formula for a relationship between X and Y. Substituting $E(0) = 36.846$ from DICE2016R as our X, we can find $\phi_{E_1}(0)$ that is likely to produce those emissions, which we further verify in GAMS. In the end, we could approximate initial emissions from DICE quite accurately, though we had to deviate somewhat from the equation 43. The parameters we got at this step were $\phi_{E_1}(0) = 0.2911$ and $\phi_{E_2}(0) = 25\phi_{E_1}(0) = 7.2764$.

Wikipedia (2020a) defines economic dematerialization as follows:

"In economics, dematerialization refers to the absolute or relative reduction in the quantity of materials required to serve economic functions in society. In common terms, dematerialization means doing more with less"

In particular, this finds reflection in constant growth of services share in global GDP (The World Bank, 2020). If this trend continues (and we have no reason to assume the contrary), the amount of energy necessary to produce an additional unit of GDP will decline further. Analyzed in terms of energy, emissions and GDP for the past decades, thus looks as follows.

According to IEA data (IEA, 2019), emissions per unit of energy, calculated as global CO_2 emissions divided by world total primary energy supply (TPES), were quite stable in 1990-2016. To be more precise, emissions per unit of energy correlate with the share of low-carbon energy sources (nuclear, hydro, biofuels and waste, geothermal, solar, etc.) in TPES, which also stayed quite flat (18.2-19.9%) over the same period of time. On the other hand, real world GDP grew 2.5 times between 1990 and 2016 (IMF, 2020), while emissions - only 1.58 times (IEA, 2019). That means that on average, CO_2 emissions per unit of real GDP declined by 1.8% annually.

Thus, on average, to produce one unit of energy, we still emit pretty much the same amount of carbon dioxide as several decades ago. However, we can produce much more with the same unit of energy today than before. We also assume that this process of dematerialization is more important than improvement in energy efficiency of fossil fuels.

7. Once the emissions in t_0 have been calibrated, we proceed to calibrating them across the whole model horizon. We assume the same dynamics of energy efficiencies of emissions in the carbon-intense and low-carbon economy, which is equivalent to setting $g\phi_{E_1}(0) = g\phi_{E_2}(0)$ and $dg\phi_{E_1} = dg\phi_{E_2}$. We make this assumption since the

economy dematerialization (producing more with less) is taking place no matter what energy source we use. This process of dematerialization is likely more important/strong than improvement in energy efficiency of fossil fuels.

8. It is difficult to find the best parameter values at this stage by picking them manually and looking how the model responds: we need to change at the same time two parameters we defined at the previous step. So we now make use of the assumptions we made in step 3 that the share of low-carbon capital equals the share of low-carbon energy and equals the share of labour in low-carbon economy. Also, in Ada-BaHaMa we effectively have $\alpha_1 = \alpha_2$ and $\theta_1(t) = \theta_2(t)$. Under both these conditions, we can show that the production function in equation 1.5 simplifies as follows:

$$Y(t) = A(t)K(t)^{\alpha_1}[\phi_1(t)E_1(t) + \phi_2(t)E_2(t)]^{\theta_1(t)}L(t)^{1-\alpha_1-\theta_1(t)} \tag{2}$$

where $K(t) = K_1(t) + K_2(t)$ and $L(t) = L_1(t) + L_2(t)$.

9. We already calibrated Ada-BaHaMa against the counter-factual baseline in section 2.2 and will make use of it now. Our targets for $Y(t)$, $E(t)$ etc. are the same as before. So we can write:

$$\begin{aligned} A(t)K(t)^{\alpha_1}[\phi_1(t)E_1(t) + \phi_2(t)E_2(t)]^{\theta_1(t)}L(t)^{1-\alpha_1-\theta_1(t)} &= \\ A(t)K(t)^{\alpha_1}(\phi_1'(t)E_1'(t))^{\theta_1(t)}L(t)^{1-\alpha_1-\theta_1(t)} \end{aligned} \tag{3}$$

where the left-hand side (LHS) refers to equation 2 while right-hand side (RHS) - to the production function from the calibration of carbon-intense economy only. $\phi_1'(t)$ means parameters from the Table 2.2 while $E_1'(t)$ - emissions that we get in Ada-BaHaMa applying these parameters.

We simplify equation 3 further:

$$\phi_1(t)E_1(t) + \phi_2(t)E_2(t) = \phi_1'(t)E_1'(t) \tag{4}$$

10. Now, instead of manually picking parameters and testing them in GAMS, we try to find them by minimizing deviation of LSH of equation 4 from its RHS. We solve the following optimization problem with Excel Solver, where the first equation minimizes MAPE:

$$Min \sum_{i=1}^{n} \left| \frac{\phi_1(t)E_1(t) + \phi_2(t)E_2(t) - \phi_1'(t)E_1'(t)}{\phi_1'(t)E_1'(t)} \right| \tag{5}$$

$$s.t. E_1(t) + E_2(t) = E_1'(t) \tag{6}$$

$$g\phi_{E_1}(0) = g\phi_{E_2}(0) \tag{7}$$

$$dg\phi_{E_1} = dg\phi_{E_2} \tag{8}$$

$$\phi_{E_1}(0) = 0.2911 \tag{9}$$

$$\phi_{E_2}(0) = 7.2764 \tag{10}$$

To make sure that the share of clean economy declines with time as it does in GAMS, we also add the following constraint:

$$\frac{\phi_2(t)E_2(t)}{\phi_1(t)E_1(t) + \phi_2(t)E_2(t)} \leq \frac{\phi_2(t-1)E_2(t-1)}{\phi_1(t-1)E_1(t-1) + \phi_2(t-1)E_2(t-1)} \tag{11}$$

With such a model formulation, we can potentially get multiple solutions, since we solve for two parameters related to energy efficiency dynamics along with two series - $E_1(t)$ and $E_2(t)$. However, we aim mainly at adjusting energy efficiency with regard to $E_1(t)$ since $E_2(t)$ progressively decay together with the carbon-free economy. To help Solver find a good feasible solution, we set final parameter values from Table 2.2 as initial values for $g\phi_{E_1}(0) = g\phi_{E_2}(0)$ and $dg\phi_{E_1} = dg\phi_{E_2}$, while for $E_1(0)$ and $E_2(0)$, we take values from the GAMS output when applying parameters obtained at step 6 of this calibration.

We get the following parameter values: $g\phi_{E_1}(0) = g\phi_{E_2}(0) = 0.1920$ and $dg\phi_{E_1} = dg\phi_{E_2} = 0.0211$. We run a model with these parameters in GAMS and conclude that they help us approximate target values quite well.