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Gotta Catch ’Em All: CCUS With endogenous technical change

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ABSTRACT

Carbon Capture Utilization and Storage (CCUS) is a pivotal technology for achieving ambitious climate targets. Despite its prominent inclusion in energy mix projections, its current deployment falls short of the required level and future uncertainties pose obstacles to its optimal diffusion. This study addresses two primary issues for the widespread adoption of CCUS. Firstly, it investigates how investments in CCUS technology either compete with or complement other green Research and Development (R&D) activity. Secondly, it explores how the heterogeneity among different economies and the peculiarities of CCUS technology itself might lead to alternative configurations compared to the current trajectory. To address these issues, this study introduces CCUS into a regional Integrated Assessment Model incorporating endogenous green R&D and heterogeneous cost functions over the 21st century. The findings reveals that undervaluing R&D costs may crowd out CCUS investments. Additionally, CCUS capital distribution by the end of the century requires substantial investments from regions with currently low deployment, such as China and lower-income countries. However, as Europe and other high income countries lose centrality in the global economy, they may become less willing to finance CCUS expansion, raising concerns about technology transfer and cost-sharing. The findings underscore the need for policies that reduce technological uncertainties and enhance international cooperation to ensure CCUS contributes effectively to emission reduction targets.

1. Introduction

Carbon Capture and Storage (CCS) or Carbon Capture, Utilization, and Storage (CCUS) are technologies designed to capture carbon dioxide (CO_2) emissions from industrial processes, e.g., power plants or factories, and secure them in long-term storage locations, instead of releasing them into the atmosphere. By preventing the release of large amounts of CO_2, these technologies play a crucial role in controlling Greenhouse Gases (GHG) emissions and therefore in the challenge of climate change mitigation (Lee et al., 2023).

Carbon capture can take place at different stages of the emissions formation (Wilberforce et al., 2021; Imran et al., 2024), and is often particularly complex and costly, especially in the so-called “hard-to-abate” sectors (Chen et al., 2022), typically the most carbon-intensive and reliant upon fossil fuels. This however raises a critical issue: since even in the context of green energy transition, fossil fuels are expected to remain a primary energy source for the foreseeable future (Huisingh et al., 2015; Nwabueze and Leggett, 2024), also in light of the current geopolitical situation (Ahmed et al., 2024), minimize their climate-altering impact is essential. In this context, the importance of CCUS becomes evident. The key role of these technologies is also highlighted by the International

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Energy Agency (IEA), which estimates that, to achieve Net Zero Emissions (NZE) by 2050, the global scale of CCUS will require a 100-fold increase from today's level of 40 Mta^{-1} (Ma et al., 2022), to contribute for 15% of emission reductions by 2050 (Bouckaert et al., 2021). Greig and Uden (2021) conducted a review of global modeling studies focusing on pathways to NZE, and on the role of CCUS in achieving this goal. Their findings highlight that achieving NZE without the integration of CCUS is often more costly, and, in some cases, unfeasible, in line with other findings in scientific literature (Jones, 2024; Zhang et al., 2024b). This is particularly true unless future technological breakthroughs address the mitigation challenges of hard-to-abate sectors. Alongside the NZE goal, it is worth noting that CCUS could also help mitigating the broader consequences of climate change, e.g., climate-related natural disasters, geopolitical tensions, and economic shocks (Yuan and Lyon, 2012). In addition, the great technological effort required to develop and implement CCUS at the global scale will also generate positive spillovers in terms of innovation and creation of green jobs.

Despite growing interest, CCUS deployment is still lacking (Chen et al., 2022). Indeed, Wei et al. (2021) estimate the need of 4.13 to 7.38 USD trillion investments in CCUS, depending on different costs trajectories, to achieve the 2 °C maximum temperature increase scenario. Additionally, Van Vuuren et al. (2017) assert that the Integrated Assessment Models (IAM) community should explore more pessimistic scenarios for the deployment of CCUS, as well as other negative emissions technologies. In scientific literature, CCUS is often incorporated in modeling attempts related to energy transition and climate change (Yu et al., 2019). However, further research is needed to better understand its behavior and possible impacts in future scenarios, in light of the intricate dynamics among economic development, technological innovation and CO_2 emissions (Comincioli and Vergalli, 2024; Zhang et al., 2024a). To the best of our knowledge, most works introduce highly detailed models, but at the cost of losing a broader, global perspective, for instance by focusing on a specific country and/or industry. Conversely, top-down optimal growth models overlook the implications of technological heterogeneity, for example in terms of cost structure. Finally, already existing IAM literature that includes detailed CCUS in a multiregional setting might not consider endogenous and directed technological change, or other key factors such as utilization.

To bridge the gaps of these approaches, in this paper we propose an extension of a global IAM, which already incorporates multiple regions and is able to represent a process of endogenous technical change: the FEEM-RICE model (Bosetti et al., 2006). More specifically, we disaggregate the endogenous energy R&D investment process in order to isolate the investment needed for CCUS development. Since the model solves an intertemporal optimization problem by setting a set of variables, including R&D and CCUS investment, it inherently accounts for the opportunity cost of each choice, ensuring that, at each stage, resources are allocated to the most effective option given. Additionally, we calibrate the regional CCUS cost structure on empirical evidence, providing a test ground for assessing regional heterogeneity within the model. This study intends to make a twofold contribution to the scientific literature. On the one hand, it examines the dynamics of investment in CCUS technology, analyzing how they may either compete or complement other green R&D endeavors. On the other hand, it investigates the complex interplay of diverse economies and the factors influencing CCUS technology, highlighting how this heterogeneity may lead to alternative developmental trajectories. The implementation of our model, properly calibrated using the most recent empirical data, allows to identify optimal trajectories for both CCUS and green R&D, as well to highlight a trade-off between them. Indeed, an incorrect assessment of R&D costs could potentially displace all investment in CCUS, confirming the outcome of previous theoretical applications such as Durmaz and Schroyen (2013). This could slow down the advancement and deployment of CCUS, raising serious doubts about achieving climate objectives and emission reduction targets. Therefore, this represents a critical challenge for policy-makers, who must ensure that green R&D investments are commensurate and not to over displace CCUS, as both are necessary for NZE. This effort would require a balanced and effective allocation of financial resources. Moreover, the geographical distribution of CCUS capital toward the end of the century underscores the importance of significant investments from currently uninvolved regions. Notably Europe and lower-income countries would require financial and technological assistance to develop better CCUS infrastructure. Despite some limitations, which are also intrinsic to RICE models, such as the oversimplified representation of R&D or the original regionalization, which we maintain for the sake of comparability, we believe the results provide valuable insights that can support policy decisions, within the unprecedented challenge of achieving NZE.

The remainder of this paper is structured as follows. Section 2 provides an overview of CCUS technology, its key features as well as its role in modeling literature, to highlight the motivation of our study. Section 3 describes the extension of the FEEM-RICE model we propose, and the experiments we carry out. Section 4 outlines the calibration process. Section 5 presents and discusses the results and following policy implications, while Section 6 concludes with final remarks and outlines directions for future developments.

2. Motivation

From a technical point of view, the captured CO_2 travels via pipeline or other means to a storage site, where it is injected into deep underground formations, typically geological formations such as depleted oil and gas reservoirs or saline aquifers. The stored CO_2 is then monitored to ensure it remains safely underground. Herzog (2011) identifies four main components of the technology: capture (separation and compression of CO_2), transport (the most economical form is through pipelines, possibly already existing), injection (depositing into the chosen geological site), and monitoring (to prevent leaks). Related technologies include Bioenergy with Carbon Capture and Storage (BECCS) and Direct Air Capture with Carbon Storage (DACCS). BECCS involves the use of bioenergy (e.g., from crops or forestry) to generate electricity or heat, with emissions captured and stored underground. The idea behind BECCS is that the CO_2 emissions from the combustion of biomass are offset by the CO_2 that is captured and stored, resulting in a net reduction of CO_2 in the atmosphere. DACCS involves capturing CO_2 directly from the air using chemical or physical processes and then storing the CO_2 underground. It is also being explored as a way to achieve negative emissions. However, both BECCS and DACCS are still relatively new technologies and face a number of challenges, including high costs and the need for large-scale deployment to achieve significant emissions reductions.

The first large-scale demonstration of CCUS technology occurred in the 1970s in the United States and was not related to climate change. Indeed, CO_2 was injected into oil reservoirs to enhance oil recovery. However, it was not until the late 1990s and early 2000s that CCUS began to be seriously considered as a way to reduce GHG emissions. Since then, several large scale CCUS projects have been developed around the world, including in the United States, Canada, Australia, and Norway. One example of the largest CCUS projects to date is the Sleipner Project, which began in 1996 and is located in the North Sea (Torp and Gale, 2004). The Sleipner Project captures and stores approximately one million metric tons of CO_2 per year in a natural gas field and has been successful in demonstrating the feasibility of large-scale CCUS.

Captured CO_2 can be employed as chemical feedstock or as injection fluids. The first use often does not sequester carbon, while injections for enhanced material recovery (EMR), e.g. for enhanced oil recovery (EOR), can partially compensate for the emissions of the recovered fossil fuel. This will be the primary meaning of ”utilization” in this work, as other industrial uses (e.g. in food and beverages) require purer (i.e., natural) streams (Tapia et al., 2018).

While CCUS has shown promise as a way to mitigate GHG emissions, it still faces significant challenges, such as high costs, public acceptance, and technological limitations. The cost of CCUS technology can vary widely depending on several factors, such as the size and complexity of the project, the type of industry and the location. The cost of a large-scale CCUS plant can range from tens to hundreds of millions of USD, and the cost per tonne of CO_2 captured can vary depending on the specific project. Estimates of the cost of CCUS vary widely, but they are generally in the range between 50 and 100 USD per tonne of CO_2 captured, although some estimates are higher. Overall, CCUS is generally considered a relatively expensive technology compared to other forms of GHG mitigation; nonetheless, the IPCC estimates that without the adoption of CCUS, mitigation costs will rise to 138% in 2100 (Ma et al., 2022). Budinis et al. (2020) report that plants with CCUS have higher costs due to the immaturity of the technology; nonetheless these could be decreasing at a rate of 2.5% per year up to 2030. Another set of issues regards the availability of storage sites and the uncertainty surrounding their permeability.

Wei et al. (2021) identify 432 sinks in 85 countries, but substantial technological and financial transfers would be required to employ them all. Lane et al. (2021) argue that deep uncertainty over the sustainable injection rate for selected sites might hinder the deployment of the technology. Indeed, the deployment of this technology in developing countries is unclear (Huisingh et al., 2015). Including the process of exploration and availability of new sinks is also seen as a primary direction of research (Chen et al., 2022). Many institutes have produced studies that consider the potential role of CCUS as a means of reducing GHG emissions. Examples include the IPCC reports, the Stern Review on the Economics of Climate Change, and reports by McKinsey. Also, many IAMs used to project future climate impacts and evaluate different policy scenarios include CCUS as one of the mitigation options. As an example of modeling, the WITCH model (Emmerling et al., 2016) includes a module of CCUS. The quantity of carbon captured is the sum of different capture technologies multiplied by specific capture rates. Cumulating these values provides the amount of storage needed. The costs for transport and storage are then a convex function of the cumulated sequestered emissions, and the total cost is the product of unit costs times the quantity of sequestered carbon.

Muratori et al. (2017) investigate the implementation of CCUS across various sectors and fuels, utilizing the Global Change Assessment model (GCAM). Their findings highlight that the adoption of CCS extends beyond the power generation sector, with a significant contributing factor being the uncertainty surrounding future technology costs. Vinca et al. (2018b) conducted a comprehensive study refining CCUS applications in electricity generation using the WITCH model. In their analysis, they modeled technological progress in CCUS through a learning rate, representing a decreasing function in installed capacity. Additionally, they introduce various CCUS technologies, including pre-combustion, post-combustion, and oxyfuel plants. Their study also considers the option of establishing new plants or retrofitting existing ones to accommodate different fossil fuels. Belaia et al. (2021) incorporate carbon capture into the framework of carbon dioxide removal (CDR) technologies within the DICE 2016 model. Their objective was to compare CCUS against geoengineering technologies in the context of a comprehensive CDR technologies portfolio.

To model CCUS in socioeconomic applications, (Dooley et al., 2002) suggest disaggregating CCUS into components and considering their costs. As a typical taxonomy, they propose the energy cost of capture, capital costs for capture and separation units, and the cost of CO_2 transport and storage.

A common assumption in the literature is that these costs will decline over time. The cost of storage can be assumed to be homogeneous over regions and time, but the latter assumption is quite strong. Moreover, the capacity limits of storage could also be considered. Yu et al. (2019) study China’s mitigation strategy through the GCAM-China model, using province-level estimated CCUS cost curves. This work provides links to the literature on cost curve estimations, most notably Dahowski et al. (2005, 2009). Smith et al. (2021) estimate costs for transportation and storage, finding that the commonly held assumption in IAMs of 10 USD per tCO_2 could underestimate the figure for given regions. Durmaz and Schroyen (2013) extend the Acemoglu model of green endogenous technical change to include a CCUS sector, finding that a green energy regime is more plausible. There exist a number of applications in partial equilibrium detailed agent-based models. For instance, Budinis et al. (2020) develop an agent-based model to characterize the investment choice of heterogeneous firms in the coal-intensive sector of ammonia production in China. With a carbon price in place firms tend to adopt a carbon capture and storage solution rather than just switching to natural gas. Han et al. (2023) study the diffusion of CCUS in a network of heterogeneous firms representing thermal plants. This concise literature review emphasizes the need for an application capable of incorporating the significant uncertainty and diversity that various regional factors may introduce. In our research, we develop a regional IAM by incorporating CCUS technology in addition to the conventional energy transition Research and Development (R&D) process, by extending the FEEM-RICE model (Bosetti et al., 2006), which was developed from the RICE-99 model of Nordhaus and Boyer (2000). RICE-99 is modeled to incorporate the interaction between an economic sector and a climate module. In particular, it differs from its previous version (RICE-96) in the functional form of the production function, i.e., a Cobb–Douglas with capital, labor and carbon-energy as inputs. Furthermore, it is an optimal growth model with a single sector. Here we adopt the income-based regionalization that characterizes both RICE-99 and FEEM-RICE. Specifically, there are 8 regions: USA, OECD Europe (EU), Other High Income countries (OHI), Middle Income countries (MI), Lower Middle Income countries (LMI), Low Income countries (LI), Russia and Eastern European (EE) and China (CN). By introducing a versatile CCUS cost function, we can effectively account for regional variations, while differentiating CCUS from other transition technologies allows us to identify fundamental trade-offs and synergies.

3. Modeling the role of CCUS technology investments

In order to study the development of CCUS investments alongside other competing practices, we extend an already established yet straightforward regional IAM. We chose the FEEM-RICE model (Bosetti et al., 2006) which, starting from RICE-99 (Nordhaus and Boyer, 2000), studies endogenous technical change in climate models, focusing on four pivotal factors: R&D investments, learning-by-doing, energy-saving, and fuel switching. Its specification features an energy technical change index dependent on learning-by-researching and learning-by-doing, impacting energy and carbon intensity. We start from this structure[1] by explicitly including a CCUS technology separated from other green technologies, as complementary to R&D.

More specifically, we distinguish between CCUS and R&D investments for two main reasons. On the one hand, we separate the Energy Technical Change Index (ETCI) from the CCUS Technical Change Index (CTCI) since they impact different phases of the production process, i.e. ex-ante and ex-post emissions. Indeed, R&D investment can lead to improvements in the energy efficiency of fossil fuel-based processes and systems (e.g., improvements in combustion efficiency, waste heat recovery, and cogeneration), as well as in developing cleaner and more efficient combustion technologies for fossil fuels (e.g., high-efficiency gas turbines, oxyfuel combustion and chemical ring combustion). These technologies can significantly reduce emissions by improving energy efficiency during the production process, while CCUS affects emissions once produced (or just before).[2] On the other hand, by separating CCUS technology from green R&D *tout court*, we can introduce an appropriate CCUS cost function that is region-specific and takes into account site-specific characteristics (11).[3] Indeed, unlike standard R&D investments, the CCUS investment cost also depends on geographic aspects such as the distribution of storage sites and their location with respect to the main economic hubs of the region (i.e. population-weighted centroids).

The $ETCI$ for region n and time t is defined as:

$$ETCI(n,t) = K_R(n,t)^a \, ABAT_S(n,t)^b, \tag{1}$$

where K_R is the stock of knowledge, $ABAT_S$ is the stock of cumulated emission abatement, while a and b are scale parameters.

The stock of knowledge K_R evolves as:

$$K_R(n,t+1) = R\&D(n,t) + \left(1-\delta_R\right) K_R(n,t), \tag{2}$$

where $R\&D$ is the investment in energy $R\&D$ and δ_R is the depreciation rate of the knowledge stock. Moreover, the stock of abatement is defined as:

$$ABAT_S(n,t+1) = \delta_A ABAT_F(n,t) + \left(1-\delta_B\right) ABAT_S(n,t), \tag{3}$$

where $ABAT_F$ is the abatement flow, δ_A is the learning factor and δ_B is the depreciation rate of cumulated experience. If these investments affect carbon intensity, reducing, *ceteris paribus*, the level of carbon emissions, the investments in CCUS aim to capture the carbon emissions once they have been produced.

The carbon capture and utilization storage technical change index for region n at time t is defined as:

$$CTCI(n,t) = CCUS(n,t)^c \, ABAT_{CCUS}(n,t)^d, \tag{4}$$

where CCUS is the stock of capital dedicated to capture activities, while $ABAT_{CCUS}$ is its amount of captured emissions. These two variables capture the amount of invested resources and the learning-by-doing in capture technology, respectively, and are described by the following two laws of motion:

$$ABAT_{CCUS}(n,t+1) = \delta_{CCUS_A} ABAT_f(n,t) + \left(1-\delta_{CCUS_A}\right) ABAT_{CCUS}(n,t), \tag{5}$$

and

$$CCUS(n,t+1) = CCUS_f(n,t) + \left(1-\delta_{CCUS}\right) CCUS(n,t), \tag{6}$$

where the current period flows update the stocks, while a part of the stocks is lost due to depreciation. The parameter δ_{CCUS_A} represents the depreciation rate for CCUS learning-by-doing while δ_{CCUS} is the depreciation rate for CCUS stock of capital.

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[1] See Appendix B for the basic functioning of the model.

[2] A common classification of the CCUS technology is to divide it into pre- and post-combustion (Zhu and Frey, 2010).

[3] By leaving the two technologies indistinguishable, it implicitly means that the presence/absence of storage sites or their distance from population centers in the region are negligible and the cost structure is the same as for other green R&D investments.

The $CTCI$, combined with the $ETCI$, reduces the emissions E of carbon energy according to:

$$E(n,t) = \varsigma(n,t)\left(\frac{1}{2 - e^{\psi_n ETCI(n,t) - \omega_n CTCI(n,t)}}\right) CE(n,t), \tag{7}$$

where ς is the level of carbon-augmenting technology in the for region n in period t, ψ_n and ω_n are region specific parameters, and CE is the carbon energy employed in region n in period t.

In addition to reducing the carbon emissions, $ETCI$ affects energy intensity by replacing the elasticity of inputs substitution in the production function as follows:

$$Q(n,t) = \Omega(n,t)\, A(n,t)\left[K(n,t)^{1-\alpha_n(ETCI)-\gamma}\, L(n,t)^{\gamma}\, CE(n,t)^{\alpha_n(ETCI)}\right] - c^{E}(n,t)\, CE(n,t), \tag{8}$$

with:

$$\alpha(ETCI(n,t)) = \frac{\theta_n}{2 - e^{\beta_n ETCI(n,t)}}, \tag{9}$$

where the parameters θ_n and β_n are calibrated to obtain the original α_n value for a given region.[4]

Finally, the CCUS technology investment and the energy R&D investment affect the accumulation of capital as follows:

$$K(n,t+1) = K(n,t)(1-\delta) + I(n,t) - \lambda R\&D(n,t) - (1-U)\left(1 + CCUS_{cost}(n,t)\right) CCUS_f(n,t) - \mu(CCUS(n,t)). \tag{10}$$

Here K is the current (depreciating) stock of capital, I is investment, $\lambda R\&D$ is the crowding-out externality following the investment in energy R&D (with $\lambda > 0$). The remainder of the equation shows how the capital accumulation is reduced by two components: the invested amount $CCUS_f$, and the operating costs of the existing carbon capture, utilization and storage technology stock, $CCUS$. The impact of efficiency and investment costs on installed capacity is more substantial compared to the influence of learning rates and operation and maintenance (O&M) costs, as highlighted by Vinca et al. (2018b). Both investment and stock costs for CCUS are to be interpreted as the green R&D counterpart, so as an opportunity cost slowing the creation of more productive capital.

Notice that the impact of CCUS investments differs in each region according to the regional-specific cost component $CCUS_{cost}(n,t)$:

$$CCUS_{cost}(n,t) = \bar{D}(n) + \left(1 - \frac{ABAT_{CCUS}(n,t)}{E(n,t)}\right). \tag{11}$$

Here the term $\bar{D}(n)$ accounts for the cost component related to the transportation of captured CO2 to potential storing sites. More specifically, this cost item captures the distance to be traveled from each country's population center (or centroid) to its closest storing facility. Regional data are then obtained as the GDP-weighted average of country-level distances, to account for the greater role of larger economies in RICE's geographically sparse regionalization. Data used to compute the centroids are retrieved from the Gridded Population of the World Version 3 (GPWv3).[5] The coordinates of potential active storage sites are then obtained by the US National Energy Technology Laboratory (NETL), providing a global collection of planned, pilot and active CCUS projects.[6] The distance is thus computed by means of the Haversine formula (Korn and Korn, 1922). This way, our region-specific cost component relies on currently active, or planned storage sites to obtain a normalized parameter. Thus, the underlying assumption is not that no more storage sites are developed over time. Instead, we assume that the current advantage held by large, advanced economies with a direct access to coastal areas and an established infrastructure connected to the fossil fuel sector, can be maintained over the course of the twenty-first century. Still, we provide a counterfactual (discussed in Appendix E), where we assume that technological breakthroughs allow developing countries to instantly catch up to advanced economies. This serves as a best case scenario in our framework. Finally, $ABAT_{CCUS}(t,n)E(n,t)^{-1}$ captures the learning-by-doing aspect of the operations, lowering the costs as long that new carbon is captured over the total emissions. Indeed, a decrease in CCUS costs due to improved maturity in the technology is to be expected (Budinis et al., 2020). This term also captures the relative weight of the fossil fuel sector over the economy GDP, such that already existing infrastructure and competences in the exploration and transportation of fossil fuels can mitigate the costs, as these countries will display an higher reduction in emissions.

Summarizing the CCUS cost function, in an extreme and unrealistic case where an economy is fully dedicated to the production of carbon energy ($CE = Q$), the distance from a storage site is zero, and all the emissions are captured, the term $CCUS_{cost}$ would collapse to zero, implying that just the invested amount would subtract from capital accumulation, without additional crowding out externalities. Vice-versa, $CCUS_{cost} > 0$ amplifies the externality. Nonetheless, this cost figure depends also negatively on the parameter U, which depicts the fraction of captured carbon which falls into utilization. Regarding the stock of CCUS, the use, monitoring and maintenance of the plants requires additional resources. Compared to standard R&D, the whole CCUS stock affects the accumulation due to the relevance of operating and maintenance costs share μ.

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[4] See Nordhaus and Boyer (2000) for the initial values.

[5] For further details, see: http://sedac.ciesin.columbia.edu/gpw.

[6] For further details, see: https://netl.doe.gov.

Table 1
Parameter values for CCUS modeling equations.

Parameters	Description	Value (%)	Source
c, d	Investment and learning-by-doing weight	50	Bosetti et al. (2006)
δ_{ccus}	Depreciation rate for CCUS stock	5	*ibid.*
δ_{ccusa}	Depreciation rate for CCUS LbD	5	*ibid.*
μ	Share of operating costs for CCUS stock	1	Author's initial guess
U	Utilization rate of captured CO_2	3	IEA (2020)

Table 2
Regionalization of the model, initial CCUS stock and normalized distances.

Region	Initial CCUS stock	Distance
China	28.308	0.162
Eastern Europe (EE)	1.378	0.854
Europe	71.631	0.0
Lower Income (LI)	0.000	0.689
Lower-Middle Income (LMI)	2.700	1.0
Other High Income (OHI)	76.163	0.12
Middle Income (MI)	17.843	0.606
USA	64.205	0.007

Note: *CCUS initial capital allocation is expressed in billion USD, retrieved from https://netl.doe.gov. Normalized distances are the outcome of an authors' elaboration, based on data retrieved from http://sedac.ciesin.columbia.edu/gpw.*

4. Calibration

To identify a solution to the model, a number of parameters need to be set to numerical values. Most parameters adopt the values of the original calibration from Bosetti et al. (2006) and Nordhaus and Boyer (2000), and are reported in Table C.1, and Table C.2 in Appendix C. Table 1 reports the values of the parameters introduced in the baseline version. Most of the parameters referring to the CCUS extension require new values. These are elaborated from empirical data when available, or according to the capital good sector as a reference. Table 2 lists the regions employed in the model,[7] and the initial CCUS capital stock. The latter figures are obtained from the IEA CCUS Project Database,[8] by aggregating active and planned plants costs by region. Fig. 1 display the global map of the storage sites employed to calculate the normalized distance in (11). In Fig. 1, green triangles are the storage sites, while the crosses represent the location of population centroids, with red circles highlighting their population. Parameter φ_n and the new parameter ω_n associated to $CTCI$ in (7). have been calibrated in order to replicate the base year in the original model and to obtain an initial cost of capture per ton (USD per ton CO_2 of 200 USD (*cfr.* Section 5.2 for a discussion of the effects of varying these parameters). The calibration procedure is fully described in Appendix D, which also presents the initial parameter values for the CCUS equations in Table D.1. Initial R&D values are also updated to reflect increased data availability on historical energy efficiency investment (IEA). Compared to the values in the original model without CCUS these values are lower, as they apply a more stringent definition of green R&D investment.

5. Results & discussion

5.1. Optimal solution of the benchmark scenario

The model is solved providing the optimal path for all the variables described above, that have been simulated until 2105.[9] In this Section we compare the results of a benchmark scenario (Scenario A), i.e. a scenario where technical change and investment include only aggregated green R&D, with the new version of the model (Scenario B), where CCUS is explicit.

Fig. 2 shows the emission intensity path in both models, for all the regions. In scenario A, this variable is decreasing, following the endogenous evolution of technological change, which results in decreasing emissions. Introducing the CCUS technology provides a slight difference for some of the regions, following the change in calibration and the other modifications. Nonetheless, the trend in emission intensities is qualitatively similar, showing a favorable environmental trend. There is heterogeneity when comparing the different regions. For instance, Eastern Europe shows a very similar trend, while USA, China and Other High income countries start very similar, but diverge from 2040 onward. The middle income (MI) region is the only one to end up with a lower emission intensity in Scenario B than in Scenario A.

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[7] Countries are divided between the regions following the original regionalization of the RICE-99 model (Nordhaus and Boyer, 2000). Further details are provided in the Appendix.

[8] For further details, see: http://www.iea.org/data-and-statistics/data-product/ccus-projects-database.

[9] All the computations have been executed with the software `GAMS 34.1.0`. Reproducibility is guaranteed. All data and code used in this study will be made available upon request.

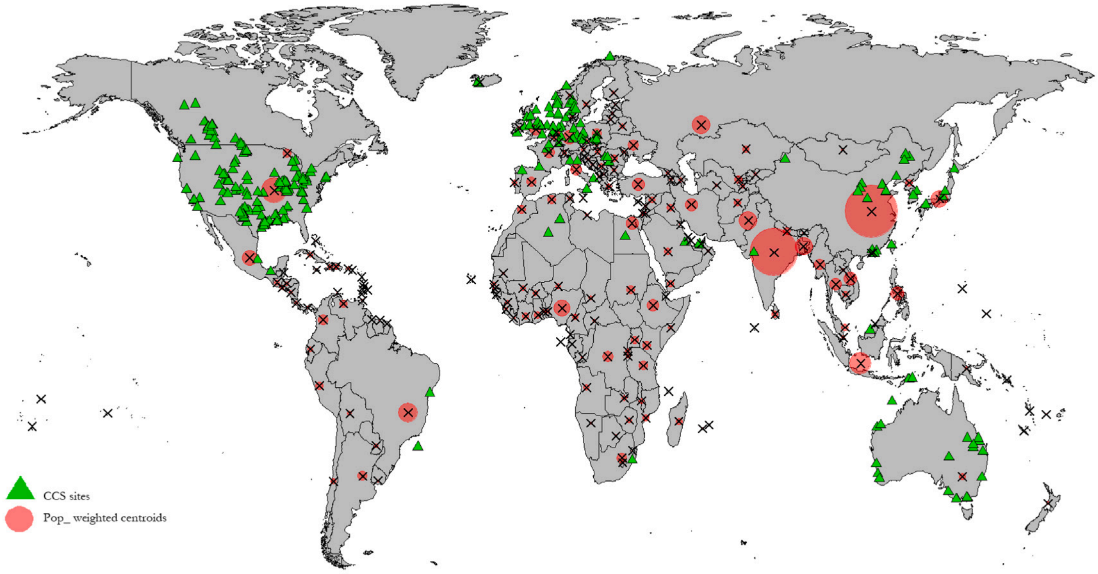


Fig. 1. Map of storage sites and population-weighted centroids of all countries.
Note: *Location of storage sites and population centroids are retrieved from https://netl.doe.gov and http://sedac.ciesin.columbia.edu/gpw, respectively.*

Table 3
Economic impacts by regions.

Region	% Variation
China	−0.61
Eastern Europe (EE)	0.12
Europe	0.08
Lower Income (LI)	−0.53
Lower-Middle Income (LMI)	−0.03
Middle Income (MI)	0.12
Other High Income (OHI)	0.26
USA	0.10

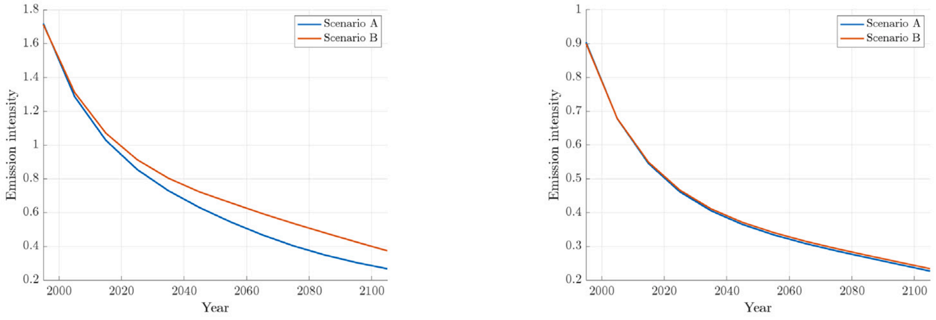
Note: *GDP variations shown are computed with respect to Scenario A. Averages are computed over the period from 1995 to 2105.*

Table 3 shows the average GDP percentage variation between the two scenarios. The introduction of the new technology provides mixed economic outcomes, although the comparison with Scenario A should consider that different values of R&D and a different parametrization have been employed. Overall, we consider this low discrepancy (always $< abs(1\%)$) as an indicator that the modeling choice of introducing CCUS explicitly does not pose significant distortions *per se*.

Fig. 3 shows the trend of GDP and CO2 emissions for the considered regions in the two scenarios. At an aggregate level, it can be observed that the introduction of CCUS has a positive impact both in terms of emissions reduction and economic growth in all regions. Specifically, the decoupling is reinforced in certain regions, such as the USA, Europe, and OHI. Indeed, these regions exhibit both a greater short-term availability of sites for capturing and storing emissions (127, 63, and 48 respectively in USA, Europe and OHI) and greater economic resources, thus enabling more investment in the CCUS technology.

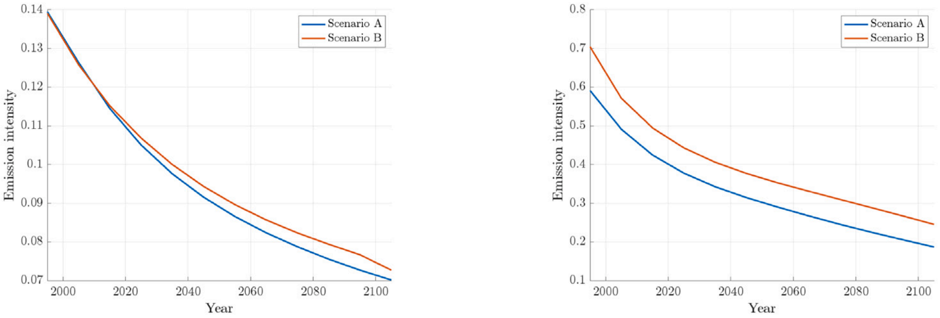
For middle-income countries, the scarcity of operating sites for implementing CCUS (only 6) seems to be a significant constraint. Despite investing at a significant level in CCUS (see in Fig. 4), they are unable to achieve complete decoupling. Indeed, Fig. 3 shows a significant reduction in the slope of the emissions trajectory for middle-income countries, but emissions continue to grow over time. The absence of economic resources and available sites ultimately contributes to the poor performance of low- and lower-middle-income countries. This might change if investments are directed to the exploration of new sinks and storage sites development.

Moreover, these distinct regional pathways are partially explained by the variability in the CCUS cost component in the capital accumulation equation yields, with certain country groups positioned to end up with more investments than others. Fig. 4 shows the level of CCUS investment at the beginning of the simulations and at the end of the century. The optimal trajectory for CCUS in Scenario B indicates that all regional groups are inclined to invest in this technology. The only exception is represented by Europe and other high income countries which, in turn, are reducing their stock of CCUS by the end of the century. A high final share is necessary by the end of the simulation for China, as well as for low income countries. The question that arises is whether these regions will have the necessary resources to pursue these investments. The impact of such a stylized heterogeneity is relevant, as



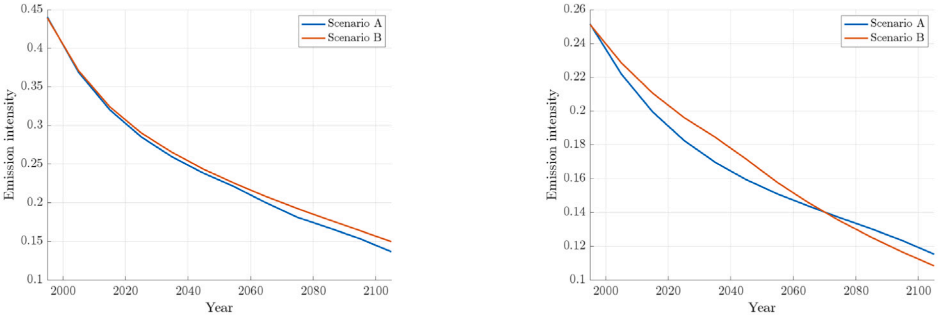
a China.

b Eastern Europe.



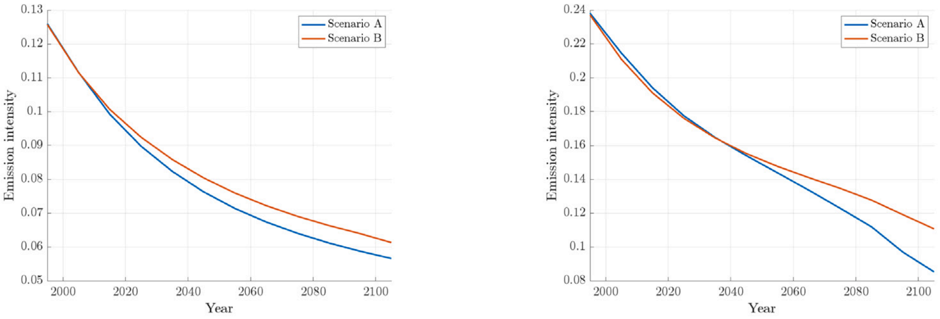
c Europe.

d Low-income.



e Lower-middle income.

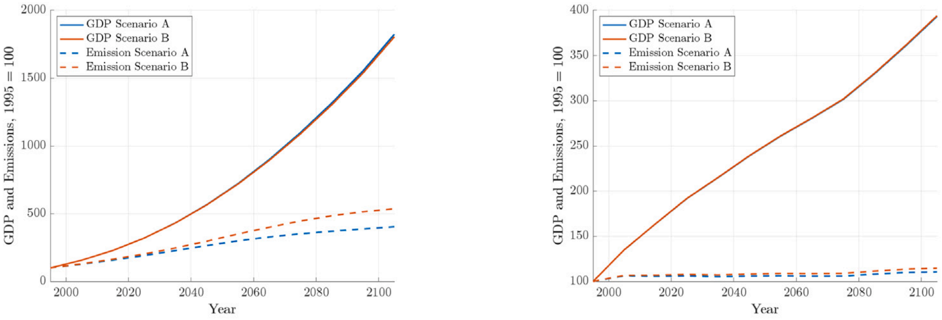
f Middle income



g Other high income

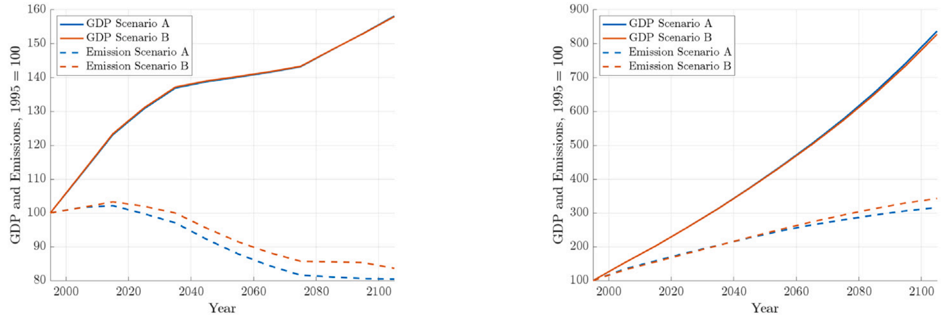
h USA

Fig. 2. Emission intensity ratio. **Note:** *Emission intensity is expressed in GtC per trillion USD.*



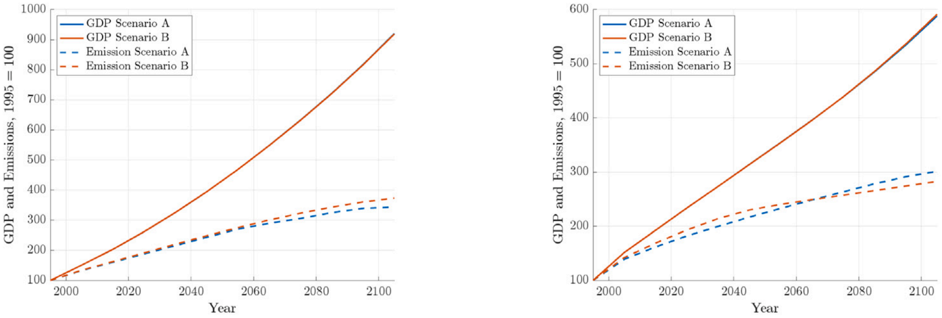
a China.

b Eastern Europe.



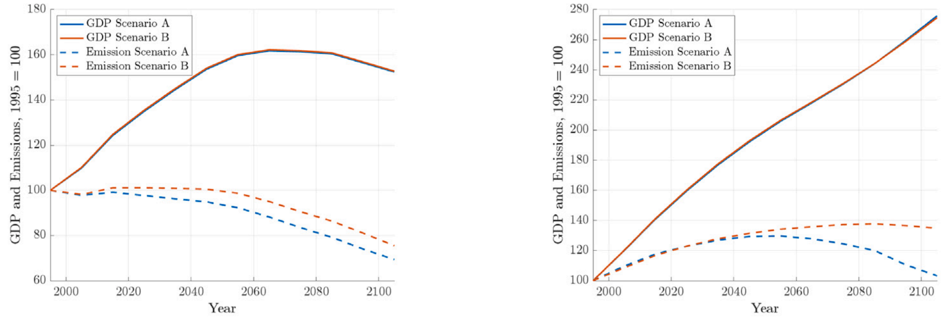
c Europe.

d Low-income.



e Lower-middle income.

f Middle income



g Other high income

h USA

Fig. 3. Evolution of GDP (solid) and emissions (dashed). **Note:** *Normalized values, setting 1995 values equal to* 100.

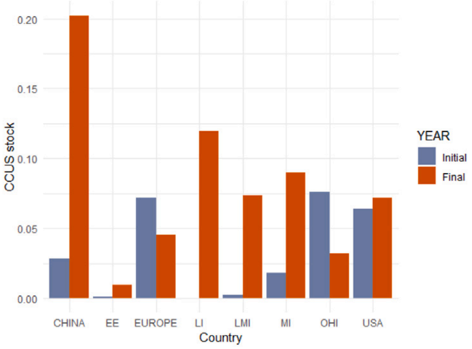
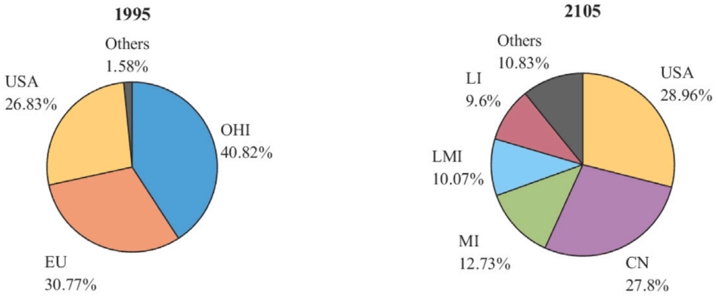


Fig. 4. Level of CCUS investment at the beginning of the simulations and at end of the century. **Note:** *Values expressed in trillion USD*.



a

b

Fig. 5. (a) Initial shares in global R&D investments, (b) Shares in global R&D investments in 2105.
Note: *Others in 1995 include: MI (0.80%), EE (0.37%), LI (0.19%), CN (0.11%), LMI (0.11%). Others in 2105 include: OHI (4.66%), EU (3.51%), EE (2.66%).*

in reality a complete and detailed characterization would require geological data for the sink type, and accounting for the different transportation modes (pipes vs. ships). Interpreting the results of Figs. 4 and 5 together, it is interesting to notice that EU and the OHI countries lose centrality in the global economy over the course of the century. These dynamics in investments in R&D and CCUS technology are driven (and followed) by periods of low economic growth or recession (see Fig. 3, with economic performance itself being influenced by demographic trends, as the EU and OHI face a structural decline in population.

This finding raises important implications regarding who should bear the responsibility of leading the energy transition and financing its costs. On the one hand, high-income regions such as the USA, EU, and OHI are currently key players in the global economy, as members of major international organizations (e.g., G7), and have high levels of investment aimed at the ecological transition of their economies. On the other hand, apart from the USA, these countries are expected to lose importance in the global economy, which could lead to a reduced willingness to share patents and costs that may exacerbate their decline and slow-down the NZE transition.

5.2. Sensitivity analysis

To improve the robustness of our results, a series of sensitivity analysis simulations with different parameter values has been carried out. In particular, we test variations of the green R&D cost externality markup parameter (λ) and the CCUS utilization rate (U). As shown in Section 5.1, there is notably a competition between green energy R&D and CCUS since both require ongoing investments and are control variables in the optimal allocation of intertemporal resources by the social planner. Externalities, represented by markups stemming from crowding out effects and CCUS investment and operating costs, influence how regions allocate their resources among different mitigation choices. Variations in these parameters, as well as in the parameter values of the efficiency in the two technical indexes, might result in different outcomes, where it is possible that the economy selects only one of the two as the optimal choice, completely crowding out the other.

Fig. 6 shows the evolution of the R&D investment for different values of the cost externality markup parameter λ, as from (10). It is evident that discounting some regional variations, R&D investment decreases when the crowding-out externalities is higher. Interestingly, Europe and Other High Income region display an R&D investment stuck to the lower historical bound.

On a similar note, Fig. 7 illustrates that the higher the markup for green energy R&D, the greater the investment in CCUS, and vice versa. This effect becomes far more evident from the second half of the century onward, and the reduction in R&D does not appear to be matched by an equal increase in CCUS investment. This discrepancy reflects the nonlinear specification of the emission intensity equation (7). Indeed, CCUS may struggle to reach a significant level or may remain confined to the lower bound if the perceived costs of other green technologies are too low. This leads us to consider that each one of the factors embedded in the CCUS structure might trigger such a scenario. Moreover, scenarios without CCUS investment might emerge when the cost of capture (USD per ton of captured CO_2) is higher, following different parametrization values of the $ETCI(n,t)$ and $CTCI(n,t)$ efficiency parameters, ψ_n and ω_n. In particular, lower values of ω_n result in higher initial costs and lower efficiency of capture. This determines a decrease in investments up to a threshold value where no CCUS investment takes place, and the whole control of emissions is left to the R&D investment. In Fig. 8, the baseline model is tested for increasing levels of utilization rate U, showing that the greater its value the greater and earlier is the investment in CCUS technology. Indeed, the utilization rate acts as a cost markup reduction, resulting in a more convenient investment.

5.3. Discussion

In Scenario B, where CCUS is actively pursued as an emission reduction strategy, at the end of the century, emission intensity decreases for all regions. However, for all regions besides MI Scenario A provides a greater decrease in emission intensity (see Fig. 2). Despite some divergence, in particular for the latter part of the century, the qualitative behavior is very similar. For example, by the end of the century, Europe shows a ratio equal to 0.070 GtC per trillion USD in Scenario A, while in Scenario B is equal to 0.072 GtC per trillion USD. A similar path is observed for OHI where emission intensity is lower in Scenario A than in Scenario B (0.056 GtC per trillion USD and 0.061 GtC per trillion USD respectively). As mentioned before, the only exception is MI where the introduction of CCUS technology allows in 2105 to reach a lower emission intensity ratio in Scenario B (0.108 GtC per trillion USD) compared to Scenario A (0.115 GtC per trillion USD).

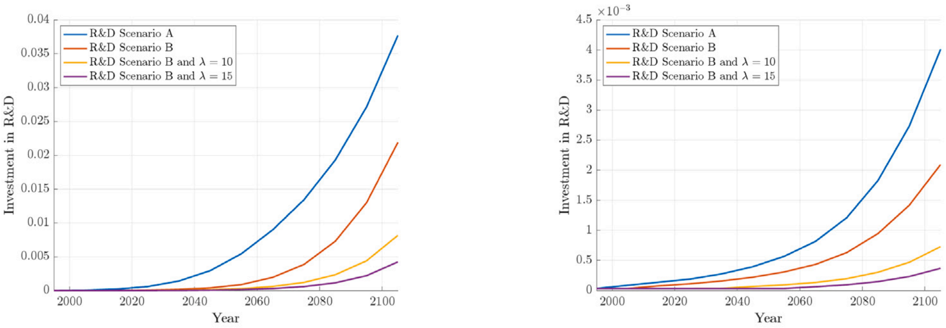
Vinca et al. (2018b) investigated the progression of electricity generation incorporating CCUS within scenarios of temperature increases of 1.5° and 2° Celsius. In the more lenient scenario, they observed a peak in technology diffusion around 2050, subsequently replaced by other renewable sources. Conversely, in the stricter scenario with a more limited carbon budget, the only present CCUS technology identified is biomass-based, chosen for its capacity to achieve negative emissions. The peak in CCUS-fitted electricity generation occurs at a maximum temperature increase of 2.5° Celsius, with no installed capacity for targets beyond 3.4° Celsius. Compared to these results we find take off after 2050 for most regions, but ongoing investments until the end of the optimization for the Europe and OHI regions.

This analysis unveils a crucial insight into the optimal trajectory of an economy that integrates CCUS investments. Specifically, it signals a shift in the final distribution of CCUS capital stock among diverse regions. Unique regional characteristics, including variations in economic structure and the location of sinks, introduce distinct development paths for this technology. Consequently, these deviations can lead to modifications in the initial distribution of capital shares. Notably, certain regions, particularly those classified as lower-middle-income or lower-income countries, will require substantial investments to align with this trajectory. This emphasizes the importance of recognizing regional nuances and directing targeted investments to ensure the equitable and effective deployment of CCUS technology. This aligns with the outcome of more detailed data-driven works such as Wei et al. (2021), that through their optimal matching exercise find that China, Europe and the US combined should account for 79% global carbon reduction by CCUS, and also confirms the need to transfer capital and technology to less developed countries. However, given the declining economic centrality of Europe (and OHI countries), these regions may become less willing to finance such transfers, particularly as their own economic and demographic challenges intensify. This reluctance could hinder global cooperation and slow down the NZE transition, exacerbating the disparities in technological access and investment between high-income and developing nations.

Conducting a sensitivity analysis on the relative weight of the cost component of the two different technologies illustrates how the social planner might opt for a mix of the two. However, there could be instances where CCUS is not even considered. In this model, green R&D encompasses both fuel switching and efficiency gains, providing additional avenues explicitly factoring in the risks and uncertainties associated with CCUS. Consequently, the potential positive impact on emission intensities could be forfeited if stakeholders choose to delay or rely on alternative technologies for similar efficiency gains without initiating substantial investments promptly. Our findings align with those of Durmaz and Schroyen (2013), emphasizing that variations in mark-ups for marginal costs preclude the concurrent development of the capture technology alongside clean energy. This observation is further supported by Grant et al. (2021), who determined that a decrease in costs for wind and solar electricity can devalue CCUS by 15% to 96%, contingent upon the specific characteristics of the energy system. In our research, we introduce an enhancement in the efficiency of green Research and Development (R&D) as a contributing factor to this reduction. Nevertheless, a complete phase-out of Carbon Capture, Utilization, and Storage (CCUS) would also eliminate its application in less substitutable contexts, such as industrial capture in the cement industry, and is therefore not advisable. Notably, Greig and Uden (2021)acknowledge the option value of CCUS, even in Net-Zero Emissions (NZE) scenarios heavily reliant on renewables. This is because CCUS can potentially address execution challenges in such scenarios, including supply chain issues, permitting complexities, and political opposition.

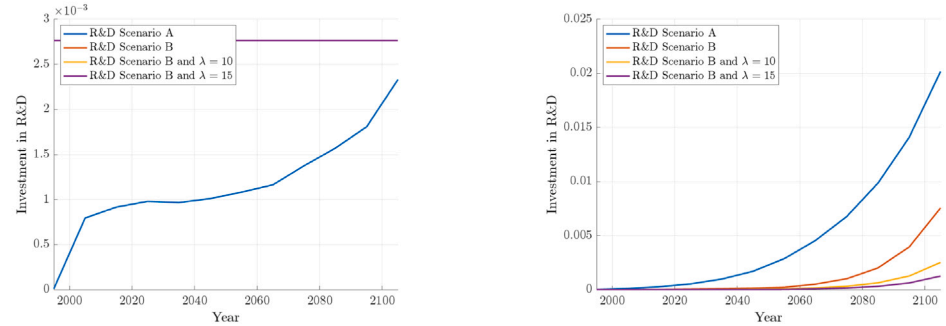
Variations in the parameters governing the CCUS cost equation can influence the investment path. Policies that reduce storage, monitoring, and verification costs and increase the utilization rate can likely prevent situations where CCUS investments fail to increase. Ideally, when possible, new emission points should be built closer to sinks, as to minimize future costs of capture. All of these measures might be insufficient without a unified carbon price policy, needed to trigger the investments (Durmaz, 2018).

Fig. 9 clearly illustrates two distinct investment trajectories for CCUS over a projected time span from 1995 to 2105, under varying policy conditions. The blue curve, which portrays the investment trajectory in an optimal model devoid of climate policy constraints (Scenario B in the previous sections), follows a more modest and gradual upward trend. This indicates a scenario where



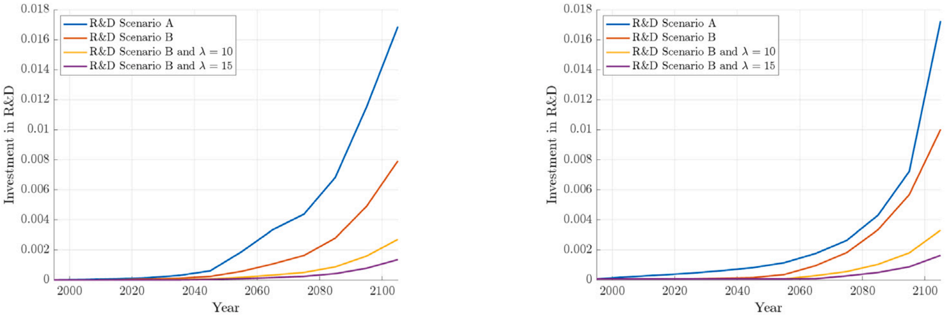
a China.

b Eastern Europe.



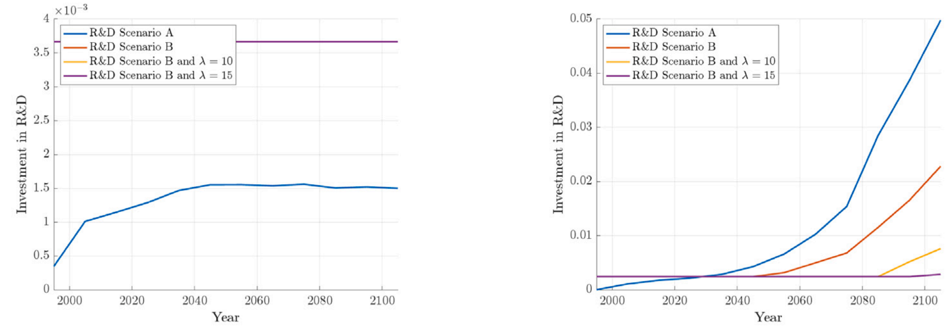
c Europe.

d Low-income.



e Lower-middle income.

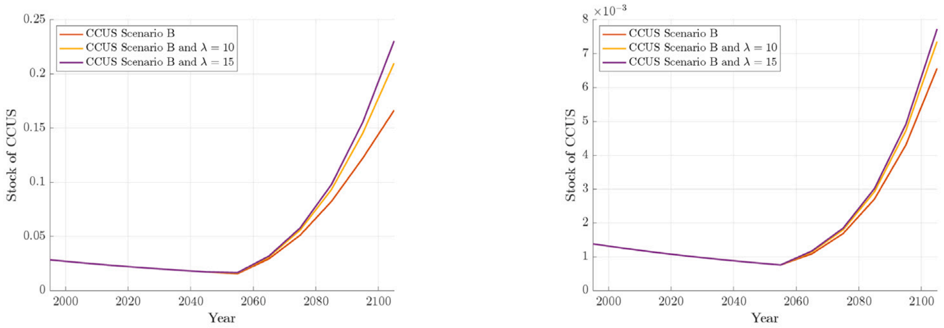
f Middle income



g Other high income

h USA

Fig. 6. R&D investment with different value of crowding out parameter λ. **Note:** *Values expressed in trillion USD.*



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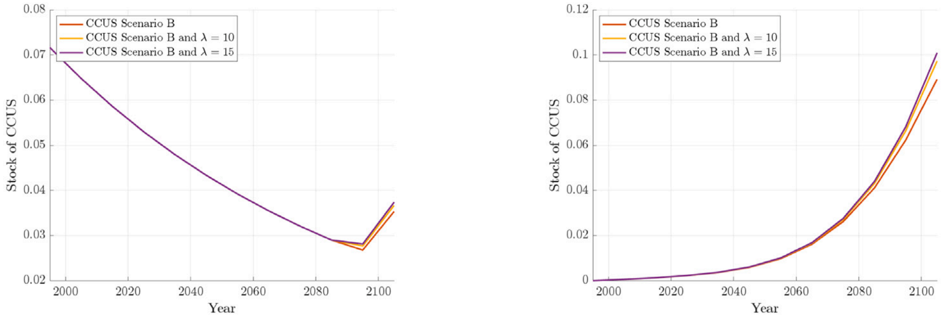
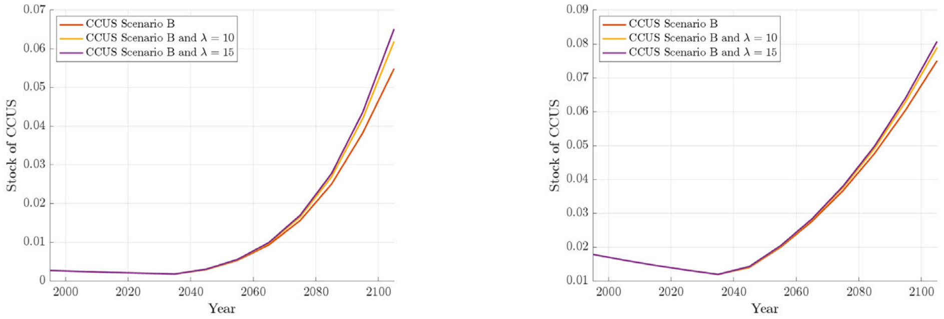


c Europe.

d Low-income.



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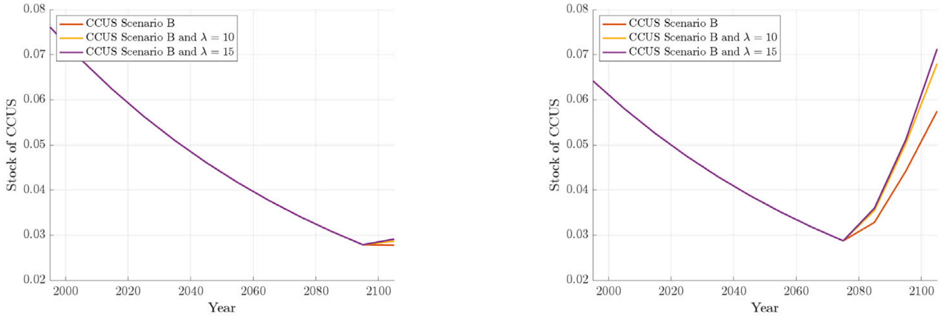
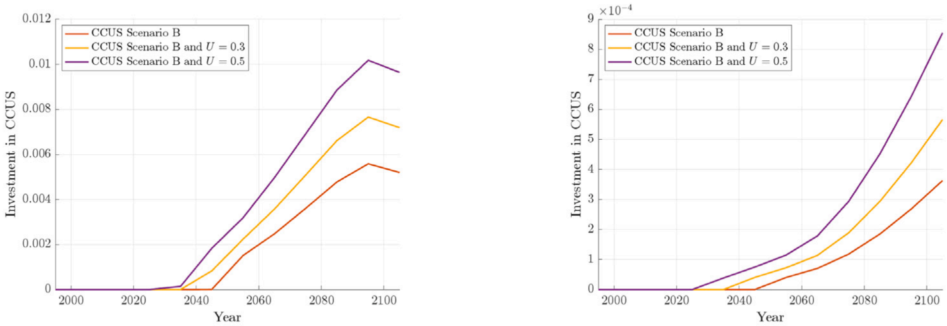


g Other high income

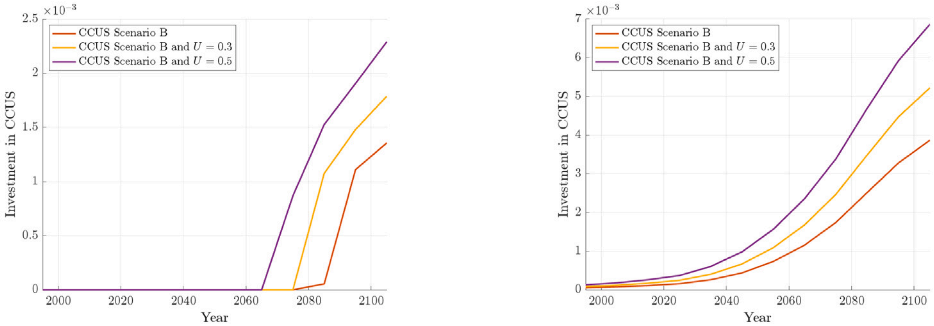
h USA

Fig. 7. Stock of CCUS with different value of crowding out parameter λ. **Note:** *Values expressed in trillion USD.*



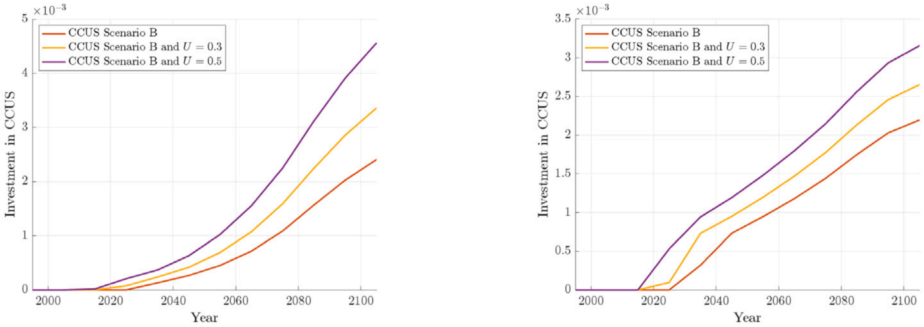
a China.

b Eastern Europe.



c Europe.

d Low-income.



e Lower-middle income.

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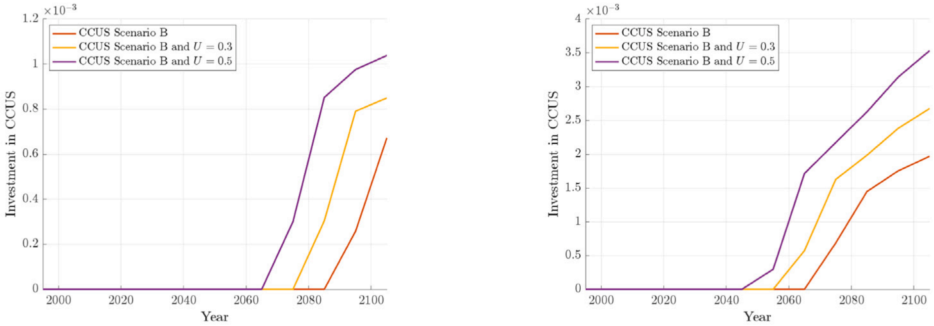

g Other high income

h USA

Fig. 8. CCUS investment with different value of utilization rate U. **Note:** *Values expressed in trillion USD.*

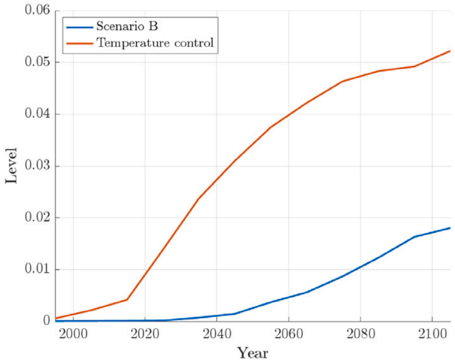

Fig. 9. Evolution of global aggregate CCUS investment, in Scenario B (blue) and control (red). **Note:** *Values expressed in trillion USD.*

investment is driven primarily by economic considerations such as cost and feasibility, without the imposition of environmental mandates asides from the impact of climate damages. Conversely, the red curve, representing investment with a temperature constraint indicative of stringent climate policy, shows a more aggressive investment pattern. This curve ascends rapidly, peaking around 2105, suggesting an accelerated deployment of CCUS technologies in response to policy-driven imperatives to meet specific temperature targets. The contrast between these curves highlights the profound influence of climate policies on the scale and timing of technological investments. The red curve's steeper rise suggests that policy frameworks mandating temperature controls necessitate a more impactful and urgent investment in CCUS technologies.

6. Conclusion

In this study, we extend the FEEM-RICE model originally presented by Bosetti et al. (2006) to account for an endogenous Carbon Capture, Utilization and Storage (CCUS) technology. To achieve this, we disaggregate the general green technology R&D sector to separate the investment in the two different components. As CCUS technology does not affect the substitutability of different production inputs, it is included only as a term capable of reducing emissions while using the same level of carbon energy. Similar to R&D, the social planner sets the optimal level of investment for the technology in each region. Each region features a specific CCUS investment costs, which depend on a variety of literature-highlighted features, such as the distance from storage sites which is empirically calibrated.

The model's optimal solution indicates that CCUS technologies have the potential to reduce emission intensity across all regions, offering an additional avenue for enhancing energy efficiency. However, the competition between the two investments is influenced by the relative weight of cost components in different technologies. Given that green R&D also impacts the fuel-switching channel, it tends to overshadow investment in CCUS, potentially leading to outcomes where the investment remains at the lower bound. If this scenario were to unfold, it could impede the realization of the most ambitious climate goals, as explicit formulations of energy mix projections consistently require a positive and substantial share of CCUS in 2050 and beyond (IEA, 2023). Our analysis identifies two primary strategies to avert this situation: avoiding overestimation of the development of alternative green R&D measures and investing in reducing CCUS relative costs through either adopting less costly technology or increasing the utilization rate of captured carbon. Furthermore, due to regional heterogeneity, the final distribution of CCUS capital shares diverges from the present one. Effective policy coordination on investment is crucial, especially for middle and lower-income countries to achieve optimal investment shares. Moreover, resources might be invested to increase the number and quality of sites in the latter. In other words, to ensure that CCUS remains an attractive alternative to other green R&D investments in the long run, policy-makers should foster research aimed at increasing carbon utilization. To ensure a fair transition, advanced economies shall share their resources and know-how with lower and middle income countries to accelerate the development of skills and infrastructures required to make CCUS a viable investment path. The sooner these infrastructures (such as carbon storage facilities and improved logistics) are available, the larger the long-term potential of CCUS investments. However, this need could clash with the economic decline that many currently high-income countries (especially in EU and OHI regions) will experience during the 21st century due to their demographic challenges. A decline that could reduce the willingness to undertake cooperative action by favoring the spread of innovation to other areas of the world. Finally, a commitment to more stringent climate policy (although problematic on a global scale from a coordination perspective) may greatly increase aggregate CCUS investments. Still, the RICE framework implies a global social planner allocating resources to optimize welfare. In reality, several policy-makers may have different objectives and adopt policies that clash with globally optimal solutions. In light of these observations, international cooperation is crucial to reach the decarbonization paths identified. This is supported by empirical investigations, that reveal coordination gaps between science, technology, and policy in carbon removal solutions (Tripodi et al., 2022).

However, this work presents some limitations. First, CCUS and R&D still appear as broad categories, potentially excluding certain technological features that might affect their mutual interaction. Second, RICE's regionalization is also somewhat broad, which means that finer segmentation might provide more precise values for the parameters governing the choice of CCUS investment.

Moreover, additional factors that might hinder the diffusion of the technology, such as public support (Chen et al., 2022), could be embedded in the model. Indeed, the lack of societal and governmental support for CCUS solutions is well known (Van Vuuren et al., 2017). Moreover, our work does not include realistic physical constraints for the considered technologies. These might span from leakage, or capture rates below 100% for CCUS, to the intermittency of electricity generation for renewable. Leakage could be a relevant source of emissions, as a leakage rate of 0.1% per year can result in 25 GtCO2 of additional emissions (Vinca et al., 2018a). To address some of this issues (e.g., efficiency, leakage, utilization rates) we performed extensive robustness checks and sensitivity analyses.

Future developments of this research will refine the analysis by expanding the current regionalization to provide more granularity. Moreover, these changes will allow us to focus more on developing countries, providing better insights on their green investment behavior.

In conclusion, our extension of the FEEM-RICE model to incorporate an endogenous CCUS technology provides a more comprehensive framework for analyzing the potential role of this technology in achieving climate change mitigation goals. By considering the heterogeneity of CCUS investment costs across regions, we have highlighted the importance of addressing regional-specific factors in the development of CCUS technology. Our results provide valuable insights for policy-makers and stakeholders as they seek to design effective policies and strategies to reduce GHG emissions and combat climate change.

CRediT authorship contribution statement

Davide Bazzana: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Nicola Comincioli:** Writing – review & editing, Visualization, Data curation, Conceptualization. **Camilla Gusperti:** Writing – review & editing, Writing – original draft, Visualization, Software, Investigation, Data curation, Conceptualization. **Demis Legrenzi:** Writing – review & editing, Investigation, Data curation, Conceptualization. **Massimiliano Carlo Pietro Rizzati:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Sergio Vergalli:** Supervision, Project administration, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

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

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Appendix A. Regional aggregation

See Table A.1.

Appendix B. Equations of the model

The model's production function is given by:

$$Q(n,t) = \Omega(n,t)\, A(n,t) \left[K(n,t)^{1-\alpha_n(ETCI)-\gamma}\, L(n,t)^{\gamma}\, CE(n,t)^{\alpha_n(ETCI)}\right] - c^E(n,t)\, CE(n,t)\,, \tag{B.1}$$

where $Q(n,t)$ is gross Output, $A(n,t)$ is total factor productivity, $K(n,t)$ is capital, $L(n,t)$ is labor, and $CE(n,t)$ is the Carbon Energy input. Damage coefficient $\Omega(n,t)$, capturing the impact of climate-induced damages on output, is discussed further below. The last term subtracts the costs associated with the production of carbon energy from gross output. Specifically, $c^E(n,t)$ represents the unitary cost of carbon-energy $CE(n,t)$ and it evolves as follows:

$$c^E(n,t) = q(t) + Markup_n, \tag{B.2}$$

where $q(t)$ is the wholesale price of carbon-energy (assumed to be equal for all regions) and $Markup_n$ is the markup on energy costs. The markup, assumed to be constant over time, accounts for regional heterogeneity in transportation, logistics costs, and fiscal regimes applied to energy. Conversely, $q(t)$ is described as:

$$q(t) = \epsilon_1 + \epsilon_2 \left[\frac{CumC(t)}{CumC^*}\right]^{\epsilon_3}, \tag{B.3}$$

where ϵ_1, ϵ_2, and ϵ_3 are constants, while cumulative consumption of carbon energy $CumC(t)$ depends on industrial emissions:

$$CumC(t) = CumC(t-1) + \Delta t E(t)\,. \tag{B.4}$$

Here $E(t)$ is global usage of carbon-energy for period t.

Table A.1
Details of the regional structure of the model.

Region	Countries
USA	US
China (CN)	CN
Europe (EU)	AT, BE, CH, DE, DK, FI, FR, GR, IT, GB, IS, IE, LU, NL, NO, PT, ES, SE
Other High Income (OHI)	AW, AU, BS, CA, GU, HK, IL, JP, NZ, VI, SG
Eastern Europe (EE)	BG, BA, BY, HR, CZ, EE, HU, LT, LV, MD, ME, MK, PL, RO, RU, RS, SK, SI, UA
Middle Income (MI)	AE, AR, BH, BR, BB, BN, CY, GA, KW, LY, LC, MO, MT, MQ, MY, NC, OM, PR, PF, RE, QA, SA, SR, TT
Lower-Middle Income (LMI)	DZ, BZ, CL, CO, CR, CU, DO, EC, FJ, FM, GP, GD, GF, IR, JM, KZ, MX, MU, MA, NA, PA, PE, PG, PY, SV, SY, TH, TM, TO, UY, VC, TN, TR, VE, VU, ZA
Lower Income (LI)	AF, AL, AO, AM, AZ, BI, BJ, BF, BD, BO, BT, BW, CF, CI, CM, CG, CD, KM, CV, DJ, ET, GE, GH, GN, GM, GW, EG, GQ, GT, GY, HN, HT, ID, IN, IQ, JO, KE, KG, KH, LA, LB, LR, LK, LS, MG, MV, ML, MM, MN, MZ, MR, MW, NE, NG, NI, NP, PK, PH, KP, RW, SN, SB, SL, SO, ST, SD, SZ, TD, TG, TJ, TZ, UG, UZ, VN, YE, ZM, ZW, WS

Note: *Regionalization based on the original model by Nordhaus and Boyer (2000).*

Labor and total factor productivity are determined by an exogenous process accounting for region-specific population and TFP growth (g_n^{pop} and g_n^A, respectively), described as:

$$L(n,t) = L(n,0)exp \int_0^t g_n^{pop}(t), \tag{B.5}$$

and

$$A(n,t) = A(n,0)exp \int_0^t g_n^{A}(t). \tag{B.6}$$

The carbon-energy coefficient in the production function is obtained as:

$$\alpha(ETCI(n)) = \left[\frac{\theta_n}{2 - e^{\beta_n ETCI(n,t)}}\right]. \tag{B.7}$$

Whereas the endogenous technical change index[10], which determines the evolution of $\alpha(ETCI(n))$ is described as:

$$ETCI(n,t) = K_R(n,t)^a\, ABAT_S(n,t)^b, \tag{B.8}$$

where K_R is the stock of knowledge, and $ABAT_s$ is the stock of cumulated emission abatement. These components, in turn, are updated according to the following rules:

$$K_R(n,t+1) = R\&D(n,t) + \left(1 - \delta_R\right) K_R(n,t), \tag{B.9}$$

and

$$ABAT_S(n,t+1) = \delta_A ABAT_F(n,t) + \left(1 - \delta_B\right) ABAT_S(n,t). \tag{B.10}$$

Regarding carbon emissions, the relationship that links it to carbon-energy in the model is described as:

$$E(n,t) = \varsigma(n,t)\left(\frac{1}{2 - e^{\psi_n ETCI(n,t) - \omega_n CTCI(n,t)}}\right) CE(n,t), \tag{B.11}$$

where ς is the level of carbon-augmenting technology for region n in period t, ψ_n and ω_n are region specific parameters, and CE is the carbon-energy employed by region n in period t. Conversely, the CCUS technical change index (CTCI):

$$CTCI(n,t) = CCUS(n,t)^c\, ABAT_{CCUS}(n,t)^d, \tag{B.12}$$

where CCUS is the stock of capital dedicated to capture activities, while $ABAT_{CCUS}$ is the connected amount of captured emissions. These two variables capture the amount of invested resources and the learning-by-doing in capture technology, respectively, and are described by the following two laws of motion:

$$ABAT_{CCUS}(n,t+1) = \delta_{CCUS_A} ABAT_f(n,t) + \left(1 - \delta_{CCUS_A}\right) ABAT_{CCUS}(n,t), \tag{B.13}$$

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[10] See Section 3 for further details concerning the equations connected to the ETCI and CTCI.

and

$$CCUS\,(n,t+1) = CCUS_f\,(n,t) + \left(1-\delta_{CCUS}\right) CCUS\,(n,t)\,, \tag{B.14}$$

where the current period flows update the stocks, while a part of the stocks is lost due to depreciation. The parameter δ_{CCUS_A} represents the depreciation rate for CCUS learning-by-doing while δ_{CCUS} is the depreciation rate for CCUS stock of capital.

The CCUS technology and the energy R&D investment affect the accumulation of capital as follows:

$$K\,(n,t+1) = K\,(n,t)\,(1-\delta) + I(n,t) - \lambda R\&D\,(n,t) - (1-U)(1+CCUS_{cost}(n,t))CCUS_f(n,t) - \mu CCUS(n,t), \tag{B.15}$$

where the equation describing the cost of the carbon capture component is:

$$CCUS_{cost}(n,t) = \bar{D}(n) + \left(1 - \frac{ABAT_{CCUS}\,(n,t)}{E\,(n,t)}\right). \tag{B.16}$$

Concerning carbon accumulation and transportation, the model employs a linear three-reservoir model. The atmosphere, the biosphere–upper oceans, and the deep oceans, each constitute a carbon reservoir. Specifically, the end-of-period mass of carbon in the atmosphere is determined as:

$$M_{AT}\,(t) = \Delta t ET\,(t-1) + \phi_{11} M_{AT}\,(t-1) + \phi_{21} M_{UP}\,(t-1)\,, \tag{B.17}$$

with $M_{UP}\,(t)$ being the mass of carbon in the upper reservoir (i.e., upper oceans and biosphere), while ϕ_{11} and ϕ_{21} are constants. In turn, $M_{UP}\,(t)$ is updated as:

$$M_{UP}\,(t) = \phi_{12} M_{AT}\,(t-1) + \phi_{22} M_{UP}\,(t-1) + \phi_{32} M_{LO}\,(t-1)\,, \tag{B.18}$$

where $M_{LO}\,(t)$ governs the evolution of carbon accumulation in the lower oceans, whereas ϕ_{12}, ϕ_{22}, and ϕ_{32} are constants. $M_{LO}\,(t)$ evolves as follows:

$$M_{LO}\,(t) = \phi_{23} M_{UP}\,(t-1) + \phi_{33} M_{LO}\,(t-1)\,. \tag{B.19}$$

with ϕ_{23} and ϕ_{33} being fixed parameters.

Conversely, the relation between GHG accumulation and radiative forcing is represented as:

$$F\,(t) = \eta\ log\left[\frac{M_{AT}\,(t)}{M_{AT}\,(t)}\right]\left(\frac{1}{log(2)}\right) + O\,(t)\,, \tag{B.20}$$

with $F\,(t)$ being the variation in total radiative forcing of GHG since preindustrial level and $O\,(t)$ being the exogenous forcing.

The increase in atmospheric temperature above preindustrial level is represented as:

$$T\,(t) = T\,(t-1) + \sigma_1\left[F\,(t) - \lambda T\,(t-1) - \sigma_2[T\,(t-1) - T_{LO}\,(t-1)]\right], \tag{B.21}$$

while the increase in deep ocean temperature is given by:

$$T_{LO}\,(t) = T_{LO}\,(t-1) + \sigma_3\left[T(t-1) - T_{LO}\right]. \tag{B.22}$$

Here, λ is a feedback parameter, while σ_1, σ_2, and σ_3 are transfer coefficients accounting for the flow rates and thermal capacities of the carbon reservoirs.

Finally, the damage function, which explain the climate economic impact on the model is described as:

$$\Omega\,(n,t) = \left[\frac{1}{D\,(n,t)}\right], \tag{B.23}$$

with

$$D\,(n,t) = \theta_{1,n}(t) + \theta_{2,n}(t)^2. \tag{B.24}$$

Here $\theta_{1,n}(t)$ ans $\theta_{2,n}(t)$ are region-specific damage coefficients.

Appendix C. Parameters calibration

See Table C.1 and Table C.2.

Appendix D. CCUS model parameter calibration

In this procedure, for each region n we begin with an initial value of ω_n and increment it in small steps (e.g., by 0.01) until the computed cost of capturing and storing one ton of CO_2 falls below a target threshold of 200 USD. Some region-specific parameters, namely $\mathrm{etci_n}$, ctci_n, ψ_n, and CA_n, are held fixed. Note that, due to limited information on the precise value of ψ_n and the potentially unrealistic effects of increased green R&D on emission reductions, we set ψ_n at a conservative value of 0.1.

Second, in the code, the exogenous technological progress is decomposed as

$$\varsigma(n,1) = \exp\left(\phi_{\mathrm{cgr},n} + \phi_n\right). \tag{D.1}$$

Table C.1
Key climate model parameters and transfer coefficients for carbon cycle and temperature dynamics.

Parameter	Description (unit)	Value	Source
$M_{AT}(1)$	Initial atmospheric concentration of CO2 (GtC)	735	
$M_{UP}(1)$	Initial concentration of CO2 in upper box (GtC)	781	
$M_{LO}(1)$	Initial concentration of CO2 in deep oceans (tC)	19 230	
$T(1)$	Initial atmospheric temperature (deg C above preind)	0.43	
$T_{LO}(1)$	Initial temperature of deep oceans (deg C above preind)	0.06	
σ_1	Speed of adjustment parameter for atm. temperature	0.226	Nordhaus and Boyer (2000)
$1/\lambda$	Equilibrium atm temp increase for CO2 doubling (deg C)	2.9078	
σ_2	Coefficient of heat loss from atm to deep oceans	0.44	
σ_3	Coefficient of heat gain by deep oceans	0.02	
ϕ_{11}	Atmosphere to atmosphere	66.616	
ϕ_{21}	Upper box to atmosphere	27.607	
ϕ_{12}	Atmosphere to upper box	33.384	
ϕ_{22}	Upper box to upper box	60.897	
ϕ_{32}	Deep ocean to upper box	0.422	
ϕ_{23}	Upper box to deep ocean	11.496	
ϕ_{33}	Deep ocean to deep ocean	99.578	
δ	Annual rate of depreciation (percent)	10	

Table C.2
Emissions, population, and productivity data.
Source: Nordhaus and Boyer (2000).

Parameter	USA	OHI	Europe	EE	MI	LMI	China	LI
Markup on carbon ($/ton)	300.00	350.00	400.00	−38.12	250.00	−2.63	−41.09	18.78
Initial carbon emissions (GtC/yr)	0.00	0.00	0.00	0.00	0.40	0.22	0.04	0.47
Initial population (million)	260.71	190.75	383.40	342.14	313.08	564.82	1198.50	2379.15
Initial population growth (%/decade)	9.00	−1.00	−6.00	1.30	16.00	20.00	8.52	24.00
Population growth decline rate (%/decade)	32.42	26.52	63.62	13.64	24.73	25.66	25.32	23.64
Initial TFP	0.0959	0.0807	0.0731	0.0171	0.0416	0.0174	0.0089	0.0075
Initial productivity growth (%/decade)	3.80	3.90	4.10	11.00	8.00	11.00	15.00	12.00
Productivity growth decline (%/decade)	1.50	0.50	1.50	4.00	3.00	4.50	5.00	4.00
Carbon share	0.238	0.093	0.157	0.117	0.068	0.088	0.138	0.101

Note: *OHI: Other High Income; EE: Eastern Europe; MI: Middle Income; LMI: Lower Middle Income; LI: Lower Income; GtC: Gigatonnes of Carbon; TFP: Total Factor Productivity; ShareCA: Share of Carbon Emissions.*

Given that $\phi_{\mathrm{cgr},n}$ is set differently for each region, the calibration procedure aims to normalize the initial value of this fraction to 1, thereby matching the calibration emission data. Accordingly, we solve for ϕ_n by finding the root of

$$\frac{\exp\left(\phi_{\mathrm{cgr},n} + \phi_n\right)}{2 - \exp\left(-\psi_n \cdot \mathrm{etci}_n - \omega_n \cdot \mathrm{ctci}_n\right)} = 1. \tag{D.2}$$

Once ϕ_n is determined, we compare the initial emissions level with the theoretical emissions resulting from a 100% increase in the value of $ctci_n$. Specifically, we define:

$$\mathrm{E}_n = \frac{\exp\left(\phi_{\mathrm{cgr},n} + \phi_n\right)}{2 - \exp\left(-\psi_n \cdot \mathrm{etci}_n - \omega_n \cdot \mathrm{ctci}_n\right)} \times CA_n, \tag{D.3}$$

$$\tilde{\mathrm{E}}_n = \frac{\exp\left(\phi_{\mathrm{cgr},n} + \phi_n\right)}{2 - \exp\left(-\psi_n \cdot \mathrm{etci}_n - \omega_n \cdot 2\,\mathrm{ctci}_n\right)} \times CA_n, \tag{D.4}$$

where CA_n is the carbon energy for region n.

The difference between these emissions, which represents the theoretical *avoided emissions* (scaled to tons of CO_2), is given by

$$\Delta\mathrm{E}_n = \mathrm{E}_n - \tilde{\mathrm{E}}_n. \tag{D.5}$$

Table D.1
Calibrated CCUS parameters by region.

Region	ϕ_n	ω_n	ψ_n	$\mathrm{CCUS}^{\mathrm{cost}}$
USA	0.0974	1.35	0.1	199
OHI	0.3525	6.33	0.1	297
EUROPE	0.1958	2.89	0.1	199
EE	0.0242	2.12	0.1	199
MI	0.2736	8.99	0.1	199
LMI	0.0478	3.07	0.1	199
CHINA	0.1156	2.47	0.1	199
LI	0.1885	4.39	0.1	199

Note: *Author's elaboration, setting* ψ_n ω_n *to reach* $CCUS^{cost} = 200$ *USD/tonne of carbon.*

By using $ctci_n$ as a proxy for the CCUS investment (denoted $CCUS_n$), noting that it may differ from the initial CCUS stock due to the functional form of $ctci_n$, and converting to dollar units, we compute the cost per ton of CO_2 abated as

$$\mathrm{CCUS}^{\mathrm{cost}}\,(\mathrm{USD/ton}) = \frac{\mathrm{CCUS}_n}{\Delta \mathrm{E}_n}. \tag{D.6}$$

The algorithm terminates once $\mathrm{CCUS}^{\mathrm{cost}}\,(\mathrm{USD/ton}) \leq 200$ (or another chosen threshold), thereby fixing ω_n at a calibrated level for each region. Table D.1 summarizes the resulting parameter values for several world regions.

Appendix E. Robustness checks

Given the methodology's stylized treatment of CCUS, various approaches should be considered to test the robustness of the proposed framework. In this Section, we introduce additional parameters and specifications to verify how CCUS deployment is affected by the introduction of frictions or facilitating factors. This should not be interpreted as a detailed exploration, which would require more refined modeling and greater heterogeneity in the parameters, but rather as a robustness analysis intended to assess the dynamics of the model.

First, we consider how the reliability and acceptability of the technology might impact the model's optimization results. Notwithstanding differences between CCUS technologies, these processes could be subject to inefficiencies, one of the main concerns being related to the possibility of leakages (Sanchez and Kammen, 2016). Moreover, public acceptance of CCUS projects could be called into question (Itaoka et al., 2005; de Best-Waldhober et al., 2009). To represent this effect we modify (6) as:

$$CCUS\,(n, t+1) = EFF \cdot CCUS_f\,(n,t) + \left(1 - \delta_{CCUS} - LEAK\right) CCUS\,(n,t), \tag{E.1}$$

with the EFF $\in$ $[0, 1]$ parameter representing inefficiencies and public/political resistance decreasing the accumulation, while LEAK $\in [0, 1]$ increases the depreciation of existing CCUS storage.

Another test is to consider factors that instead might favor the investment in CCUS. In particular, in this work we are assuming a purely competitive relationship between CCUS and green R&D (by definition of the latter). However, the assumption of not having a single spillover between the two technology could be relaxed and explored. We hypothesize a complementary component that, from green R&D, could foster CCUS technologies. An example could be the use of cheaper renewable energy in reducing the Opex of one capture plant (Rubin et al., 2007). This means that an increase in green R&D even if separated could also lower the cost component CCUS(T,n). So we can define a new CCUS cost component as:

$$\mathrm{CCUS}^{\mathrm{COMP}}(T, N) = \mathrm{CCUS}(T, N) - \alpha^{comp} \cdot \mathrm{RAD}(T, N), \tag{E.2}$$

where α^{comp} is a parameter affecting the degree of complementarity between the two technologies, $\mathrm{CCUS}(T, N)$ is the baseline CCUS cost, $\mathrm{RAD}(T, N)$ is the green R&D investment at time T and region N. This component substitutes $\mathrm{CCUS}(T, N)$ into the capital accumulation Eq. (10).

Finally, the evolution of exploration technologies and storage site usage might lead to the discovery of new sites, reducing the distance component of our cost specification in (11). Recognizing the uncertainty regarding the future evolution of this component, we propose a theoretical experiment where the discovery of an overabundance of sites leads to a decrease to 0 of the distance cost component $\bar{D}(n)$. This can serve as an extreme boundary for assessing the impact of distance in this particular model.

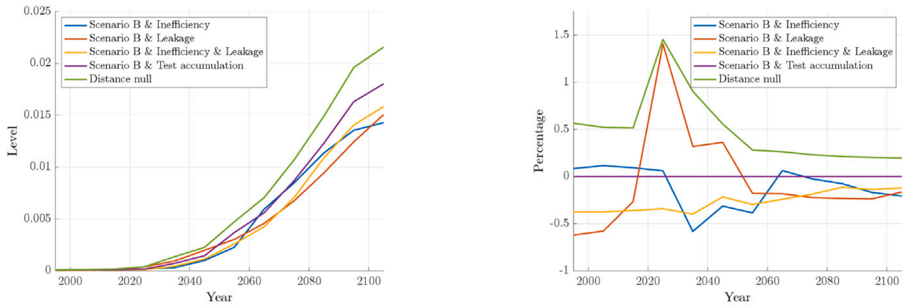
Table E.1 summarizes the proposed experiments and reports the calibration of the introduced parameters. It must be noted that the chosen values are necessarily guesses on the conservative side. For instance, leakages values are usually described in the literature to be closer to 0.01%, making our chosen value closer to the upper spectrum of the estimates.

Fig. E.1 depicts the results of the proposed experiments for selected variables, showing cumulated CCUS investment and cumulated emissions for all experiments in both absolute levels and percentage variations against benchmark scenario B. The introduction of inefficiencies in CCUS capital accumulation reveals an interesting dynamics: a slight increase until 2020 followed by a significant drop from 2030 to 2060, highlighting the presence of critical thresholds for CCUS deployment, yet paradoxically resulting in lower emissions compared to the benchmark. Introducing leakages instead, results in an initial negative difference followed by an acceleration up until 2050. This also the case with the greater increase in emissions. The Test Accumulation scenario shows minimal deviation from the baseline in both investment and emissions, suggesting that higher complementarity parameter values

Table E.1
Summary and description of the robustness experiments and calibration values of their parameters.

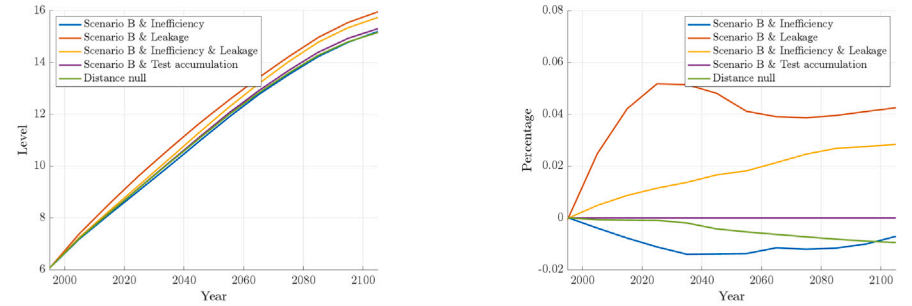
Experiment	Description	Parameter	Value (unit)
Inefficiency	Introduced an inefficiency parameter in (6)	EFF	80 (%)
Leakage	Introduced a leakage parameter in (6)	$LEAK$	2 (%)
Inefficiency and Leakage	Introducing both inefficiency and leakage parameter in (6)	$EFF, LEAK$	80,2 (%)
Distance null	Setting $\bar{D}(n) = 0$ in (11)	–	–
Test accumulation	Introducing a complementarity component in (10)	α^{comp}	5 (%)

Notes: *All experiments introduce their modifications on the B scenario.*



a Cumulated CCUS investment.

b Percentage variations of CCUS investment.



c Cumulated emissions.

d Percentage variations of emissions.

Fig. E.1. Results showing the impact of parameter variations on CCUS investments and emissions.
Note: *(a) Cumulated CCUS investment across scenarios; (b) Percentage variations in CCUS investment relative to the baseline; (c) Cumulated emissions profiles under different parameter settings; and (d) Percentage variations in emissions compared to the reference case. All percentage variations in panels (b) and (d) are calculated relative to Scenario B (baseline). CCUS investments are reported in USD trillions and emissions in gigatonnes of carbon (GtC).*

should be considered to alter the dynamics, though at the cost of losing the distinctiveness of green R&D from CCUS. Finally, the figure reveals that eliminating distance costs in the Distance null scenario significantly enhances CCUS capital accumulation in the economy, spiking to 150% around 2025 before gradually declining to approximately 20% by 2090, demonstrating the substantial impact of geographic constraints on deployment rates. This results in a decrease in emissions which however, is far lower in order of magnitudes, probably explainable by compositional effects in the abatement technology and economic effects.

Data availability

Data will be made available on request.

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