PNAS

Supporting Information for

Modeling direct air carbon capture and storage in a 1.5°C future using historical analogs

Morgan R. Edwards[a,b]*, Zachary H. Thomas[b]* Gregory F. Nemet[a,b], Sagar Rathod[a,b,c], Jenna Greene[b], Kavita Surana[d,e,f], Kathleen M. Kennedy[e], Jay Fuhrman,[g] Haewon C. McJeon[h]

a. La Follette School of Public Affairs, University of Wisconsin–Madison, Madison, WI 53706
b. Nelson Institute Center for Sustainability and the Global Environment, University of Wisconsin–Madison, Madison, WI 53726
c. Office of Sustainability, University of Wisconsin–Madison, Madison, WI 53715
d. Institute for Data, Energy, and Sustainability, Vienna University of Economics and Business, 1020 Vienna, Austria
e. Center for Global Sustainability, School of Public Policy, University of Maryland College Park, MD 20742
f. Complexity Science Hub, 1080 Vienna, Austria
g. Joint Global Change Research Institute, Pacific Northwest National Laboratory, College Park, MD 20740
h. Graduate School of Green Growth & Sustainability, Korea Advanced Institute of Science and Technology, Daejeon 34141, Republic of Korea

Corresponding author: Morgan R. Edwards

Email: morgan.edwards@wisc.edu

This PDF file includes:

Supplementary Notes 1 to 6
Figures S1 to S21
Tables S1 to S3
SI References

Table of Contents

A. Supplementary Notes

Supplementary Note #1: Modeling Technological Change

The potential to achieve high levels of CDR will ultimately depend on the characteristics of the underlying technologies and their social and environmental context. Technology adoption processes can be understood using a multi-level perspective, which describes how regime shifts in global innovation systems emerge from interactions and feedbacks between *niches* (the protected contexts that support an emerging technology), *regimes* (the current set of technologies, rules, and actors), and *landscapes* (trends in the broader nature-society system). Change in these systems is often nonlinear: regimes are set up to reinforce the status quo but may be disrupted when a tipping point in technology performance (e.g., costs) or the system landscape (e.g., climate policy) is reached. Case studies on innovations with different socio-technical characteristics are contributing to nascent theory on how linkages between technologies, markets, policies, and society shape innovation dynamics (1). For example, studies have highlighted the role of technology features such as modularity, complexity, and customization in accelerating technology improvement and adoption (2, 3).

Representing new technologies and technological change in IAMs is difficult because these models are cumbersome to update and computationally expensive. However, the innovation literature has developed many techniques to model technological innovation. Previous work has represented innovation using statistical fits to historical data on technology costs, performance, and patents as a function of time or cumulative production (4–6). Other approaches resolve the components of technology cost changes and incorporate constraints based on engineering limits, commodity prices, and other factors (7–9). Expert elicitations have also been conducted on a wide range of technologies (10–12) (including DACCS (13)). Recent work suggests that statistical models outperform expert predictions (6), and models using only a small number of parameters perform well for key energy technologies such as wind and solar (although they may lack explanatory power). Researchers have also conducted meta-analyses of cost declines and proposed that progress across technologies may be used to improve predictions of technological change and characterize uncertainties (14, 15). This approach is particularly important for new technologies, where there is limited data on which to base predictions.

Technology adoption in systems models is an emergent property that is determined by how the model represents both technology characteristics and the broader systems context in which the technology operates. Technology characteristics typically include cost and input requirements (e.g., energy, materials) as well as parameters that capture heterogeneity in technology preferences and represent the phase-in of early-stage technologies. These characteristics may be static or change exogenously (as a function of time) or endogenously (as a function of production). The ability to represent context is a key benefit of systems models. IAMs in particular have detailed representations of interactions across sectors and between technical, economic, and natural systems. Nevertheless, evaluations of the outputs of these models (based on innovation theory, empirical data, and expert opinions) have been mixed. They can be slow to incorporate some technological and societal innovations (e.g., demand-side solutions (16)) while imagining high uptake of others (including CDR). Notably, they may overestimate growth rates for some technologies (e.g., nuclear energy and carbon capture and storage) and underestimate it for others (e.g., wind and solar) (17, 18).

Supplementary Note #2: Defining the Formative Phase

Modeling the early phases of innovation is challenging for novel technologies because progress is irregular and highly uncertain and empirical data is sparse (19–22). Research typically distinguishes between two early phases of innovation: (1) the invention stage, where a new idea is discovered or created, which is not included in models of s-curve shaped growth and (2) the formative stage where potential adopters decide to use an existing idea, which is typically included in growth models dating back to Rogers's original formulation (23, 24) but which some researchers leave out due to high uncertainty (25). We include the formative phase in our growth model (see Supplementary Note #3). There are many metrics for the start of the formative phase; one common metric is the first of at least two sequential years of capacity additions (19). For DACCS, this occurred in 2015 when Carbon Engineering constructed a pilot plant in Canada, followed in 2016 by a Climeworks plant in Switzerland (26, 27). Other metrics identify the start of the formative phase as the time when a new technology displaces a small fraction of an incumbent technology, anywhere from 0.1%-10% (17, 22, 28–30). However, in contrast to clean energy technologies, metrics based on incumbent replacement are difficult to apply for CDR because there is no clear incumbent technology.

There are also large uncertainties in the duration of the formative phase for new technologies, which can be irregular and highly uncertain (28). One definition of the end of the formative phase is the time when adoption reaches 2.5% of the final saturation level, which is consistent with Rogers' framework where "innovators" adopt the first 2.5% of a technology (21).[1] As with other metrics of fractional adoption, this metric can be applied to clean energy technologies that have a clearly defined market (31). However, defining this market for DACCS is challenging. Using our estimate of a total market for CDR of 15.9 $GtCO_2$ (see Section D), its formative phase would end when cumulative capacity reaches 398 $MtCO_2$. If all currently proposed DAC plants are successfully built, total capacity could reach 113 $MtCO_2$ in 2035. Consequently, the length of the formative phase depends on future growth beyond current plant announcements. Our baseline model results place the end of the formative phase at 2040 (using offshore wind as an analog) and 2076 (using natural gas pipelines as an analog). This results in a length of the formative phase of 25-61 years. For comparison, Bento and Wilson's 2016 analysis finds a mean length of the formative phase of 22 years for energy technologies, with a range of 4-85 years for the central estimate and 4-168 across all indicators (28).

Supplementary Note #3: Foundations of the S-Curve

The concept of the s-curve, now widely used in modeling technology adoption over time, began in the study of biological growth in which growth is capped by resource availability (32) and was first applied in an agricultural context (23). In the 1960s, researchers applied an s-curve model

[1] Another metric for the end of the formative phase is the time when a 10% threshold of maximum unit capacity is reached. This metric requires knowing the maximum unit capacity. However, it is plausible that the duration of the formative phase for DACCS could be shorter under this definition, given for example the large 1 $MtCO_2$ plant designed by Carbon Engineering scheduled to begin operation in 2025.

to study the diffusion of technologies and the hypothesis of different stages of growth emerged (21). When applied to technological growth, the conceptual foundations of s-curve shaped growth are similar to, but distinct from, the application to biological growth. The growth process begins after the invention stage (a long and generally unpredictable process, see Supplementary Note #2) and proceeds in three phases, which are identified by the slope of the curve: formative, growth, and saturation (21, 22, 33). A logistic growth model is frequently used to represent the s-curve and both calculate technology growth rates (e.g., to compare growth across technologies or between models and historical data) (17, 34–36) and to project growth into the future (22, 30, 31, 37–40).

When used to compare technology growth, the explicit-form logistic function is fit to technology capacity data to extract the fit parameters that together predict capacity *C(t)* over time: the growth rate *k*, the inflection year t_0, and the saturation level *L*:

$$C(t) = \frac{L}{1+e^{-k(t-t_0)}}. \quad \text{S1}$$

Another metric for comparing growth over time is the time taken to get from 10% to 90% of the market share saturation (19, 22, 30, 41), which can range from 5 to 70 years or more (41):

$$\Delta t = \frac{\ln 81}{k}. \quad \text{S2}$$

To project future growth for more mature technologies, logistic growth can be extrapolated based on existing capacity data. This method of projection is most accurate for data series that include the inflection point, or are very close to this point (22, 42).

For early-stage technologies without sufficient data (i.e., where growth has not yet approached the inflection point), the logistic substitution model can be used to model future growth. The logistic substitution model projects displacement of an incumbent technology in an existing market by modifying the differential form of the logistic equation (see (37)):

$$\frac{dC(t)}{dt} = kC(t)\left(1 - \frac{C(t)}{L}\right). \quad \text{S3}$$

At small capacity *C(t)*, the rate of change is approximately exponential. As capacity increases, the rate of change decreases to zero as capacity saturates at *L*. The discrete form of the logistic substitution model can be used with a small time step (e.g., one year) to iteratively calculate future capacity for an early stage technology (22, 30, 31, 34, 37, 39, 40):

$$C_t + \frac{dC_t}{dt} = C_{t+1} = C_t\left(1 + k\left(1 - \frac{C_t}{L}\right)\right). \quad \text{S4}$$

Projecting technology growth using the logistic substitution model thus requires choosing three parameters: an initial capacity C_0, a growth rate k, and a saturation level L. This approach can model the initial diffusion of multiple new technologies but implicitly assumes only one incumbent (and saturation level) can exist in each market (22, 34).

The parameters C_0, k, and L in the logistic substitution model can be determined using different information sources. Typically, C_0 is determined using early data on the target technology, k is determined using growth rates from another, more developed technology[2], and L is determined by estimates of market size (22, 30, 31, 34, 37, 39, 40). We discuss our approach to identifying these parameters in the Materials and Methods and in Section D. Here we briefly highlight the advantages of the logistic substitution model over other extrapolation approaches. The most common alternative approach is to use a constant growth rate (43–46) to project or constrain growth. This approach implicitly assumes there are no limits to demand and is not consistent with observations of s-curve shaped technological growth. Another approach, which is not typically used but offers a comparison point to the logistic substitution model, is to extrapolate logistic growth directly using two fit parameters (t_0 and k) from another technology. With this approach, which then solves for L, the saturation level is highly dependent on the details of the fit and inflection year (31) and is not tied to market demand. This can also lead to unrealistically high (or low) projected levels of adoption. (We discuss the sensitivity of our feasibility space to uncertainties in the parameters in the logistic substitution model in Section F.)

Supplementary Note #4: Overview of the SHARD Method

We use the Systematic Historical Analogue Research for Decisionmaking (SHARD) method to explore how historical outcomes for analogous technologies can inform assessments of DACCS adoption potential (47). Drawing on theory and approaches from history and transitions research, SHARD provides a systematic approach for using historical analogs to provide insights on low-carbon technologies. It does this by matching relevant characteristics of a target innovation to a historical analog. A strength of the method is that it allows for transparent and reliable comparisons between technologies not only for quantitative aspects like growth rates but also for other factors less amenable to quantification but that have proven to be consequential. An initial test case illustrating the SHARD method focuses on understanding potential obstacles to adoption of plant-based meat and how to reduce them (47). Other recent work has applied this method to biochar, another CDR method (15).

Here we use SHARD for a different application – to improve the design of integrated assessment model scenarios for climate change mitigation. We select historical analogs for this application using the three-step SHARD process:

1. **Clarify the objectives of the study.** These objectives are used to develop a list of characteristics for matching the target innovation with a historical analog. Innovations and analogs need not (and, practically, cannot) share all possible characteristics; rather, SHARD focuses on identifying technologies with strategic similarity. Different analogs can be selected to capture different characteristics (e.g., engineering process, infrastructure requirements, social and political urgency, etc.).

---

[2] The logistic substitution model (Equation S4) is an iterative, numerical solution to the differential form of the logistic equation (Equation S3). However, this form makes it more computationally challenging to fit because the numerical solution must be calculated iteratively to measure the error of the fit parameters. Since the growth rate of the two forms is identical, we fit the historical technology capacity data to the explicit form of the model and project DACCS growth numerically using the logistic substitution model.

2. **Develop a long list of historical analog candidates.** This list may be derived from a larger dataset of possible analogs or by brainstorming a list of analogs that have the potential to share similarities with the target innovation.
3. **Select historical analogs.** The selection of analogs is determined by the objectives of the study and corresponding target characteristics as well as practical considerations such as data availability and completeness (if these have not already been addressed in the identification of the long list).

Theory supporting the development of the SHARD method highlights the value of understanding innovation as a complex adaptive system, in which technology changes generate nonlinear outcomes and activities in apparently inconsequential niche markets can catalyze regime-level transitions (48). Taking into account the full set of influences on one indicator (e.g., growth in adoption over time) provides a way to transfer insights on technological innovation from history in a way that is suitable for systems modeling.

There is a rich literature for researchers to draw on when identifying target characteristics for historical analogs. The multi-level perspective divides features of technologies and their use context into different levels – niche, regime, and landscape – that can influence rates of adoption (49). Drawing on this perspective, SHARD identifies several dimensions to consider when identifying historical analogs: (1) technological and infrastructural characteristics, (2) economic and financial characteristics, (3) policy and political characteristics, (4) social and cultural characteristics, and (5) user and consumption characteristics (47). Other work has identified a wide variety of technology characteristics that may determine rates of growth and improvement over time (8, 50). One recent framework develops a two-dimensional technology typology based on degree of complexity and need for customization to guide policies for low-carbon innovation (3). Other work uses historical analogs that are less tied to particular features of technologies but intended to explore or bound adoption pathways for new technologies using historical examples of rapid innovation (e.g., solar photovoltaics) or emergency deployment scenarios (e.g., wartime mobilization) (37, 47, 51).

Supplementary Note #5: Overview of the Feasibility Literature

Integrated assessment models are important tools for exploring the feasibility of climate action. From a modeling perspective, a scenario is typically considered feasible if a solution can be found, for a given model structure and set of inputs (which vary within and across models) (52). Policies (e.g., a temperature target and/or carbon price) are typically set exogenously, but analysts may also design these scenarios to reflect political constraints (53–55). Feasibility from a modeling perspective is thus different from feasibility in the real world. Pathways that are feasible in a model may in fact be infeasible if the model does not adequately capture various barriers to climate action. Previous work has raised this issue for growth in low-carbon technologies in general and for CDR in particular, especially with regards to social and political barriers that may arise outside the technical and economic features that are the focus of many models (56, 57). Pathways that are infeasible in a model may also be feasible in the real world if the model does not adequately represent different potential levers for climate action (e.g., development of novel climate technologies or broad societal transformations).

Engagement with fields outside systems modeling can refine notions of feasibility and may expand or contract the feasibility space. The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report introduced a comprehensive framework for understanding the feasibility of climate actions by assessing barriers and enablers across six dimensions: geophysical, environmental-ecological, technological, economic, sociocultural, and institutional (58). Feasibility in this framework is an evolving feature of climate actions. For example, public policies can increase the likelihood that a climate action reaches its full mitigation potential by removing critical barriers or supporting enabling factors. However, the framework also emphasizes the importance of a comprehensive feasibility assessment and notes that policies targeting individual barriers or enablers may have limited or no effect if other important barriers are overlooked. The most critical barriers can also be context specific. For example, the higher up front costs of renewable energy projects may be a larger barrier in low- and middle-income countries with a higher cost of capital (43, 59).

Other literature has sought to refine the concept of feasibility or use examples from history to assess feasibility across different dimensions. Pathways to reaching policy targets (e.g., limiting the rise in global temperatures to 1.5°C) have been a major focus of integrated assessment modeling as well as broader feasibility studies (60). These studies also emphasize that feasibility depends on context (e.g., by exploring the feasibility *of what*, *when and where*, and *for whom*) (61). The IPCC defines feasibility as the “potential for a mitigation or adaptation option to be implemented,” a concept that differs from the modeling concept of feasibility as solvability (62). Another recent review defines feasibility as “do-able under realistic assumptions” and differentiates it from plausibility (“occurable in exploratory scenarios with internally-consistent assumptions”, more closely related to model solvability) and possible (“imaginable under disruptions”) (51). One approach to defining these realistic assumptions is to compare modeled transition pathways with analogs from history and/or evaluate whether these pathways may be historically unprecedented (15, 63, 64).

Our study connects closely with this feasibility literature, particularly recent work defining feasibility spaces (37, 51), by using historical analogs to model adoption pathways for DACCS in an integrated assessment model. One strength of this approach is that observed growth rates for historical analogs are the combined result of all barriers and enablers and thus implicitly capture the complexities and interactions highlighted in recent feasibility discussions (58). This is particularly helpful for modeling adoption of CDR technologies such as DACCS because these technologies often serve as a backstop mitigation technology in IAMs (52). Consequently, modeled CDR adoption may be relatively insensitive to large variations in the technical and economic features (such as cost and efficiency) that are represented in models, despite the fact that these features can be important barriers to technology adoption in the real world. IAMs such as GCAM use share weights to capture gradual introduction of novel technologies, beginning at 0 for DACCS in 2020 and increasing to 1 by 2050, at which point DACCS competes purely on cost (65).

Supplementary Note #6: CDR in GCAM versus Other IAMs

Analyses of large ensembles of scenarios for limiting the increase in global temperature to 1.5°C or well below 2°C suggest that some amount of CDR will be required to offset emissions from hard-to-abate sectors and reach net-zero or net-negative CO_2 emissions (66). However, the level of CDR envisioned across scenarios varies widely. For example, CDR in scenarios in the AR6 Database ranges from 0-19 $GtCO_2$ in 2050 and 0.1-28 $GtCO_2$ in 2100 (see also Figure 4b). Additionally, the AR6 Database represents scenarios that were submitted as of July 2021, when many scenarios (69%) had yet to incorporate DACCS or other forms of CDR beyond land use change and BECCS. DACCS was also not included in initial IAM exercises conducted as part of the Shared Socioeconomic Pathways (SSPs) (65). As CDR generally serves as a "backstop" in IAM scenarios, a key driver of the level of CDR in model scenarios is the ease of reducing residual emissions (67). The structural treatment of geologic carbon storage on which both BECCS and DACCS (as well as fossil fuels with CCS) depend as static, effectively unlimited resources with no scaling or annual capacity constraints can also drive large CDR and residual emissions projections by IAMs (68, 69).

Important levers for reducing residual emissions include energy efficiency, demand reduction, and non-CO_2 greenhouse gases. While recent work has focused on low energy demand scenarios (16), non-CO_2 emissions are relatively understudied, yet they potentially comprise over half of residual emissions (70, 71). The levels of CDR in IAM scenarios may change in the future with increased representation of (a) CDR methods, including their practically achievable growth rates, which we designed this study to explore, and (b) levers for reducing residual emissions. Currently, GCAM is on the higher end of the range of IAMs in terms of the levels of CDR featured in scenarios to meet 1.5°C or well below 2°C goals. While we are unaware of a comprehensive study comparing the drivers of residual emissions (and, consequently, CDR) across IAMs, the level of emissions reductions from land use change and non-CO_2 emissions sources likely play important roles. GCAM uses a logit approach to represent competition for land use and barriers to land use change and, optionally, includes a price on CO_2 emissions from the land sector (which we include in our simulations). Non-CO_2 emission reductions are represented with varying degrees of detail across IAMs, and recent work with GCAM highlights the opportunities and limits of deep mitigation of non-CO_2 emissions (71).

The fact that the levels of CDR featured in GCAM are on the higher end of IAM scenarios makes GCAM an appropriate IAM for our analysis, as it enables us to represent the full feasibility space for DACCS, including the high end as well as the low end of the feasibility range, using growth rate constraints from different historical analogs.

B. Historical Technology Analogs

We begin our selection of historical technology analogs with a set of 147 technologies from the Historical Adoption of TeCHnology (HATCH) database 1.0 (15, 72). HATCH includes data on technology adoption over time (in native units) sourced from a variety of public data sources such as data annexes from published papers, datasets from institutions such as the U.S. Energy Information Administration and International Energy Agency, and in some cases custom-built time series from multiple data sources. It contains data on technologies across ten categories (labeled by the authors): agriculture, chemicals, digitalization, energy storage, energy supply, household appliances, infrastructure, materials, space and defense, and miscellaneous. We also make three updates to the dataset: (1) we add a dataset on global gas pipelines as the existing dataset in HATCH contains only U.S. data (73), (2) we update the data on ammonia synthesis to be consistent with HATCH 1.5 (72), which is more complete than HATCH 1.0, and (3) we update the data on natural gas liquefaction capacity to a more complete dataset (74). This brings our set of potential analogs to 148.

Our process for identifying a set of historical technology analogs for DACCS from the modified HATCH dataset (described in the previous paragraph) consisted of several steps. We show the full list of potential technology analogs, filtering steps, and logistic growth rates in Supplementary File 1 and our long list of technologies (after applying our data quality screening steps described in the next paragraph) in Supplementary File 2. Using the SHARD method (47), we aim to arrive at a list of analogs that is transparent and reproducible. However, HATCH does not represent the universe of all possible technology analogs, and there is necessarily some expert judgment in selecting analogs. Future researchers may identify a different set of analogs, with implications for the calculation of the feasibility space for DACCS. Additionally, given our goal of defining the feasibility space, we erred on the side of including analogs where there was a reasonable justification for doing so. Other analyses, for example using detailed historical methods to understand the potential barriers and enablers to growth (e.g., (47, 75)), would likely require a more restrictive filtering approach.

First, we perform three data quality screening steps to develop a long list of potential analogs. Specifically, we filter the list to technologies that have at least 20 data points, global adoption data, and units of capacity. These filters reduced the dataset from 148 technologies first to 96 (length filter), then to 74 (global scope filter), and then to 64 (capacity filter). The capacity filter is important because it allows us to appropriately assess growth in cases where unit size varies. Many technologies have either explicit units of capacity (e.g., wind capacity or miles of pipeline) or units that are closely related to capacity (e.g., annual production of chemicals and materials) (15). However, other analogs do not. For example, analogs such as nuclear weapons and satellite launches were eliminated during this phase because each unit can have a very different size. Similarly, several digitization technologies were eliminated because they were in units of performance (e.g., transistors per microprocessor) rather than capacity. We also eliminated one technology (nitric acid production) that had data quality issues[3] and removed two (oil production and nitrogen fertilizer) that were similar to but less complete than another technology (oil refineries and ammonia synthesis), bringing the final long list of technologies to 61.

Second, we conducted a detailed review of the remaining 61 technologies to identify a short list of 20 representative analogs for DACCS. An overarching criteria was for technologies to share some similarity to DACCS in terms of (1) technological and infrastructural characteristics (i.e.,

[3] Global nitric acid production data in HATCH 1.0 was calculated by summing production data from different national datasets with time intervals, resulting in production values that oscillated over time, particularly in early years. Given these quality issues, we did not include nitric acid in our long list.

complex technologies in centralized or modular systems, with different degrees of customization or mass-customization) and (2) user and consumption characteristics (i.e., industry as customers for carbon credits or CO_2 in a nascent, non-concentrated market, rather than individual consumers). The eliminated categories include:

1. Agricultural products: Technologies in this list (cane sugar production, aquaculture production, and capture fisheries) are agricultural commodities and processes. They lack the technological and infrastructural characteristics of DACCS.
2. Household appliances: Technologies in this list (cellphones, washing machines, laundry dryers, and refrigerators) are purchased directly by individuals or households. They lack the user and consumption characteristics of DACCS.
3. Personal transportation: Technologies in this list (bicycles, motorcycles, and passenger cars) are purchased by individuals or households and lack the user and consumption characteristics of DACCS.
4. Insufficient market size: Technologies in this list (concentrated solar power, on-grid marine energy, and sodium-based batteries) have insufficient market size to ensure that technologies will scale. For these technologies, early growth rates may not be representative of sustained growth potential.
5. Not a manufactured product: Technologies in this list include raw materials or mining (e.g., copper, cobalt, graphite) that do not result in a manufactured product. These technologies lack the technological and infrastructural characteristics of DACCS.
6. Low technological similarity: Beyond the categories above, we also eliminated technologies that had low technological similarity to DACCS across other dimensions. For example, we eliminated technologies that were simple and standardized (e.g., steel and silver production) or rely on very different types of processes and inputs (e.g., polystyrene and polyvinylchloride which are organic compounds formed from polymerization reactions, and latent heat storage where materials undergo phase changes rather than chemical reactions).

Finally, we grouped the remaining 20 technologies into six categories: chemicals and materials, fuel production, fossil fuel energy, low carbon energy, enabling technologies, and transport and infrastructure. We further assessed each of these technologies and compared them to DACCS characteristics across the five dimensions of SHARD: (1) technological and infrastructural characteristics, (2) economic and financial characteristics, (3) policy and political characteristics, (4) social and cultural characteristics, and (5) user and consumption characteristics. Each of the identified analogs shared at least one additional similarity to DACCS (besides our previous filters on technology and infrastructure and user and consumption characteristics). We summarize the characteristics of DACCS in Box 1 and list the full set of analogs with brief descriptions in the text. For conciseness, we do not repeat the general similarities that were used to identify these technologies in the previous filtering step. Note that we also include solar PV, although it does not share the complexity of DACCS, given its common use as a bounding case in literature assessing potential growth in novel technologies (37, 47, 76).

Box 1: Characteristics of DACCS

- Technology and infrastructure characteristics
  - Liquid (L-DAC)
    - High complexity and multiple steps for chemical processing.
    - Customized or mass-customized.
    - High operating temperature (~900°C).
    - Large, centralized plants with economies of scale.
  - Solid (S-DAC):
    - Similar complexity to L-DAC
    - Less customized compared to L-DAC.
    - Lower operating temperature compared to L-DAC (~100°C).
    - Modular facilities with smaller economies of scale.
  - Storage:
    - Siting is optimal near specific geological formations.
- Economic and financial characteristics
  - Product (CO_2) has low intrinsic value. Existing markets are limited to niche applications (e.g., beverage carbonation, e-fuels) that are decentralized and unlikely to be viable on their own.
  - Pricing schemes are needed to define the cost of CO_2, such as with carbon taxes, cap and trade, regulations, or other guarantees to raise financing.
  - Current demand for CO_2 capture with permanent storage is for carbon credits.
- Policy and political characteristics
  - Regional variation among policy initiatives. Current policies are mostly related to incentives for financing and demonstration projects.
  - Incentive to site capture within political boundaries to achieve net-zero targets, even when siting is not optimal for technical reasons.
  - High political urgency for net-zero (in some locations, with potential for urgency to be further heightened in the future).
- Social and cultural characteristics
  - Portrayed as a climate backstop, where rapid adoption could enable continued use of incumbent technologies such as fossil fuels.
  - Portrayed as expensive and risky because it has not deployed at large scale.
  - Social license: may see delays due to public protest and opposition.
- User and consumption characteristics
  - Consumers are industry/companies, especially in the early stages.
  - Companies either buy carbon credits or the CO_2 for use (nascent market).
  - The market is fairly concentrated with a few large purchasers.

List of analogs with brief descriptions (with the growth rate in parentheses):

1. Chemicals and materials:
   a. *Aluminum refining (4.7%):* The Hall-Héroult process used for aluminum production operates at temperatures between 900-1000°C (77), similar to L-DAC.

This similarity in temperature range could imply similar requirements for heating technologies and energy use.

   b. *Cement production (4.9%):* Cement production shares technological similarities with L-DAC processes. Calcination is the central reaction in cement production and is also one of the key steps in L-DAC operation.
   c. *Ammonia synthesis (8.7%):* Ammonia synthesis shares technological similarities with DAC in that it uses an ambient atmospheric gas (N_2) as an input. Pressure swing adsorption processes that can be used to generate hydrogen used in ammonia production are also similar to adsorption/desorption processes used in some S-DAC technologies. Additionally, ammonia production has high socio-political urgency (due to the global importance of fertilizer and munitions) and may be an analog for DACCS under urgent climate action.
2. Fuel production:
   a. *Motor gasoline (8.9%):* Motor gasoline is the product of large chemical engineering processes, as is also the case with DACCS, with demand driven by a specific application. Additionally, DACCS may enable continued use of motor gasoline and other liquid fuels under climate policy.
   b. *Ethanol production (12.9%):* Ethanol production is a large, multi-step chemical engineering process, similar to DACCS. There may be incentives to site production within political boundaries for energy security reasons. Additionally, ethanol production can also enable the continued use of existing fossil fuel infrastructure, which may also be the case with DACCS.
   c. *Oil refineries (13.4%):* Oil refineries involve large chemical engineering processes where some steps such as steam cracking take place at high temperatures similar to L-DAC. There can also be incentives to site refineries within political boundaries for energy security reasons. Oil refineries are a key element of fossil fuel energy systems whose continued use may be enabled by DACCS.
3. Fossil fuel combustion:
   a. *Steam engines (6.9%):* Stationary steam engines are a mature technology used in a variety of applications, including manufacturing and power generation (including fossil fuel and other thermal power plants). Given their important role in legacy energy systems and possible links to continued use of fossil fuels, they represent a potential analog for DAC adoption drivers.
   b. *Natural gas plants (9.0%):* Natural gas plants are a key fossil fuel energy technology whose growth may show similarities with DACCS. Additionally DACCS may enable extended use of natural gas.
   c. *Coal power plants (10.9%):* As with natural gas plants, coal power plants are a key fossil fuel energy technology. Additionally DACCS may enable extended use of coal power plants.
4. Low carbon generation:
   a. *Hydropower (6.7%):* Hydropower is a large, capital intensive infrastructure project, similar to DACCS. As with DACCS, it may also be an important technology for reaching net-zero and other climate policy goals.

b. *Nuclear energy (22.5%):* Nuclear energy is large and capital intensive with a complex regulatory environment, potentially similar to DACCS. As with DACCS, it is also an important technology for reaching net-zero goals.
c. *Onshore wind (23.6%):* Wind energy is mechanistically very different from DACCS (not limited by chemical inputs or energy requirements) but shares some similarities in that it involves multiple components of varying complexity and can be design-intensive or mass-customized (3, 78). Wind shares more similarities with DACCS in terms of the role of policy, where wind technologies were initially not cost competitive and needed policy support across the innovation system for technology development and market deployment. It was also initially considered risky and is an important technology for reaching net-zero goals.
d. *Offshore wind (29.3%)*: As with onshore wind, offshore wind shares some technological similarities with DAC as well as policy similarities (in terms of the need for policy support) and is important for reaching net-zero goals.

5. Enabling technologies:
    a. *Lead acid batteries (7.4%):* Lead acid batteries are found in a wide range of energy storage applications, automobiles with internal combustion engines and for backup energy storage. While some of these uses could extend the use of fossil fuel infrastructures, battery storage more broadly (including different battery chemistries) will be an important enabling technology for enabling clean energy transitions and reaching net-zero goals.
    b. *Pumped hydro storage (16.5%):* As with battery energy storage, pumped hydro storage is a potential enabling technology for clean energy transitions and will be important for reaching net-zero policy targets. It is also a large, capital intensive infrastructure project, similar to DACCS.
    c. *Coal scrubbers (18.3%):* Removing sulfur dioxide (SO_2) from coal power plant effluent via wet flue gas desulfurization is a chemically difficult task given low concentrations (typically 0.2-5% by dry weight) and corrosive by-products (79), which presents similarities to the difficulty of removing CO_2 at low concentrations from ambient atmosphere. Early attempts to remove SO_2 were unreliable and expensive, but regulations in especially Japan and the U.S. incentivized the development of scrubber technology, leading to cost declines and widespread, global adoption (80). Emissions regulations for CO_2 could incentivize similar deployment of DAC. Scrubbers are also an enabling technology for continued use of fossil fuels, which may also be true for DACCS.
6. Transport/infrastructure:
    a. *Natural gas pipelines (3.2%)*: Pipeline infrastructure will be required for DACCS that is displaced from geological storage. Pipelines require administrative, legal, and regulatory frameworks for land acquisitions and rights of way and may also see delays due to public protest and opposition.
    b. *Natural gas liquefaction (9.3%)*: Long distance CO_2 transportation is most effective in a dense-phase or supercritical state. Either method needs compression and pumping in multiple stages to achieve operational parameters. This process can find analogs to LNG liquefaction trains involving coolant

compression trains in multiple stages as well as heat exchange and phase changes of natural gas. As with pipelines, natural gas liquefaction plants can also see delays due to protest and opposition to this infrastructure.

   c. *High speed rail (15.5%)*: Construction of high speed rail represents an analog for CO_2 transportation that is subject to permitting and social license. While it potentially poses less environmental risk, administrative, legal, and regulatory frameworks for site selection, land acquisition, and rights-of-way are still required, as with pipelines. It also represents a major class of infrastructure projects that can be important for net-zero and may require up front policy support.

7. *Solar photovoltaics (PV, 31%):* Solar PV is relatively standardized, mass produced, and scaled primarily through learning-by-doing, making it less similar to DACCS in terms of technical characteristics (3). However, as for wind, early market creation (including in some niche markets) and deployment has largely been enabled by policy incentives as technologies were not initially cost competitive with fossil fuel alternatives. Solar is also an important technology for reaching net-zero. Growth rates for solar may represent an upper bound for DACCS that may or may not be achievable in practice given the large differences in complexity and customization requirements of the two technologies.

We then fit the time-series annual capacity for each of the technology analogs to a logistic growth function to extract growth rates and project DACCS capacity. Figures S1-S2 show the raw data and logistic fits for each of the analogs. The black dots show raw data (cumulative capacity of each analog over time in its native units). The blue lines show the logistic fit (calculated by minimizing the sum of squared residuals using the curve_fit function from the Python SciPy package v.1.10.0 (81)).[4] Background on the logistic growth equation as a foundation for the s-curve is provided in Supplementary Note #3.

[4] Note that, for some analogs, there are minor differences in the calculated growth rates compared to those published in HATCH 1.0 due to differences in the fitting software.

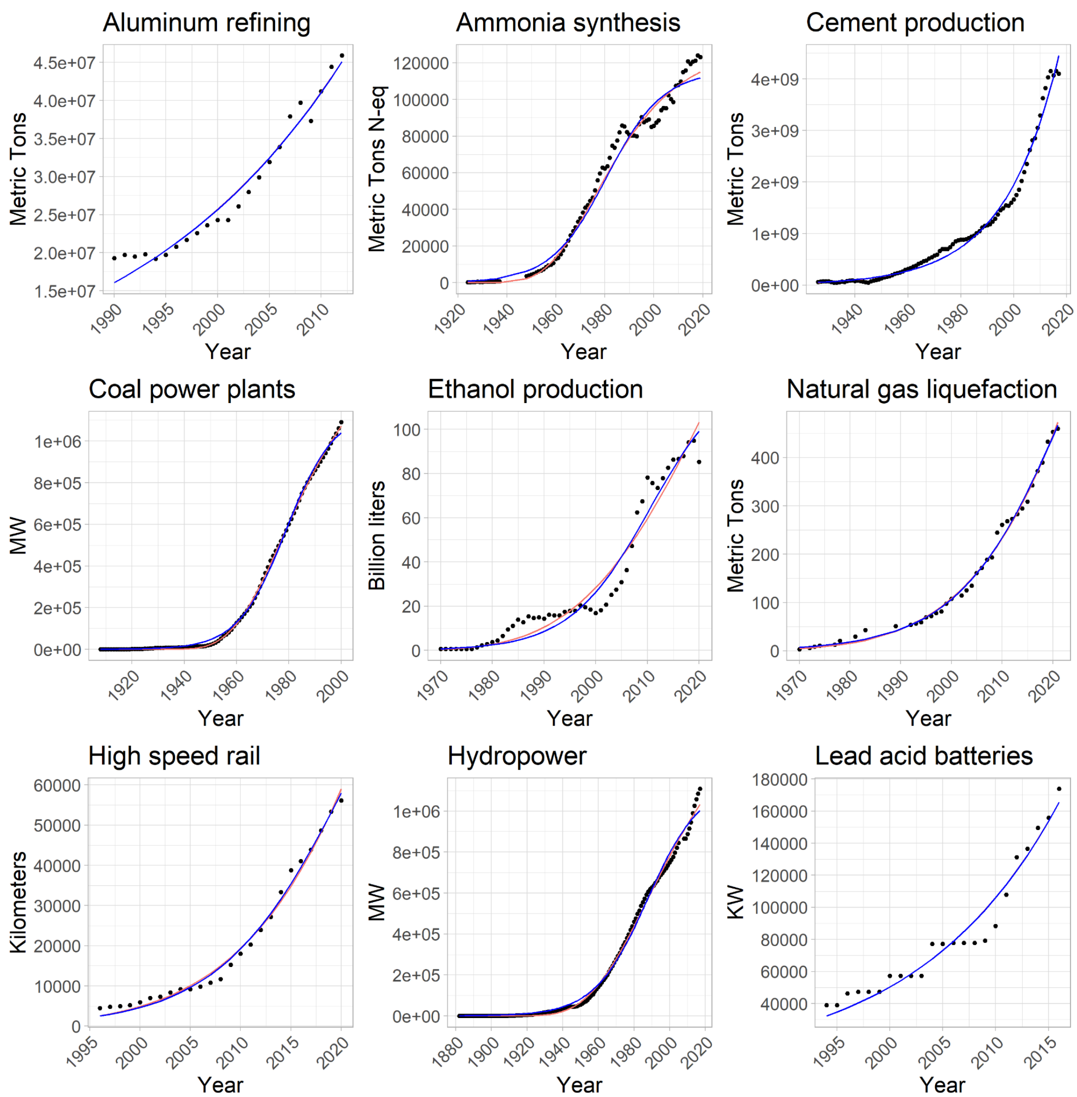

Figure S1*: Historical capacity data (black points), logistic fits (blue lines), and Gompertz fits (red lines) for selected DACCS analogs.*

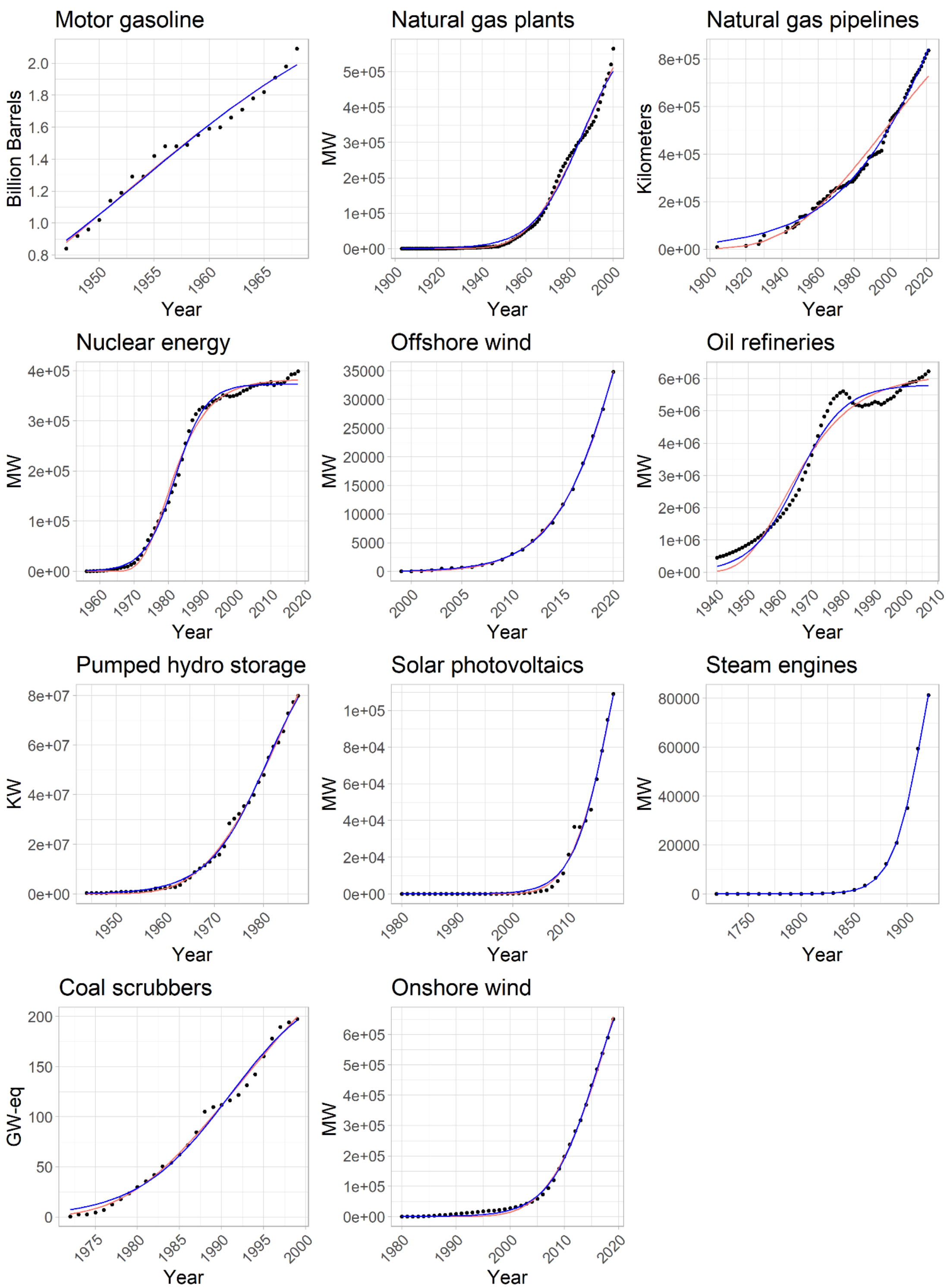

***Figure S2**: Historical capacity data (black points), logistic fits (blue lines), and Gompertz fits (red lines) for selected DACCS analogs. Note that the Gompertz fit for the steam engines analog did not converge and is not included in the figure.*

C. Empirical Data on Early Adoption

Here we present early empirical data on DAC[5] adoption using estimates of plants that are (a) operating, (b) under construction, and (c) announced. We source data on operating and planned plants by first compiling a list of DAC companies from multiple recent IEA reports (26, 82, 83), the 2023 State of CDR report and associated database (84), cdr.fyi (85), i3 (86), Stripe (87), government funding initiatives (88, 89), and Google searches for DAC news and announcements (see Table S1). From this list of companies, we construct a dataset of past and planned capacity installations by searching company websites and news articles for plant start-up dates and capture capacity projections. Some capacities are reported as company-wide targets that include multiple plants, such as Carbon Engineering's goal to build 100 1 $MtCO_2$ plants by 2035. Plants are designated under construction if they have not started operation but have received a Financial Investment Decision (FID) to begin construction; this does not include Front-End Engineering and Design (FEED) funding or advance purchases.

Plants with insufficient operational or capacity information are not included, such as CarbonCollect's plan to deploy an unspecified number of 4 $MtCO_2$ capacity plants within the next ten years (90). We also do not include information about planned capacity from reports and databases if these plans could not be verified on a company website (for example, if links cited were broken and information about the company was not be returned in a Google search), or if the information on the company was updated as construction plans changed. For example, one database reported that HIF Global would capture 2.2 $MtCO_2$ annually starting in 2026 to synthesize e-fuels, but more recent reports suggest that the DAC unit will be integrated later (91, 92). We also do not include announcements that do not specify when the plant will become operational. Removing these plants has minimal effects on the total projected capacity, with the possible exception of CarbonCollect, which has announced plans for "farms" that could capture 1-4 $MtCO_2$ but does not specify how many or when they would become operational (90).

Overall, our data cleaning process expands the number of announced DAC plants compared to those listed in recent reports (26, 82, 83). However, our estimates of plants that are operating or under construction are similar to the State of CDR report (84). The DAC innovation system is rapidly evolving, with many new announcements occurring even over the course of our analysis. Our database reflects a snapshot of current expectations as of September 16, 2023, and we recognize these expectations may change in the future.

Table S1: *List of operating and forecast DAC plants*

Company	Country	Year	Operating capacity (tCO_2)	Technology	Status	Source

[5] As in other sections, we use the term "DAC" rather than "DACCS" to refer to early adoption as not all current and planned plants incorporate permanent CO_2 storage.

Global Thermostat	United States	2010	500	S-DAC	Operating	(26)
Global Thermostat	United States	2013	1000	S-DAC	Operating	(26)
Climeworks	Germany	2015	1	S-DAC	Operating	(26)
Carbon Engineering	Canada	2015	365	L-DAC	Operating	(26)
Climeworks	Switzerland	2016	50	S-DAC	Operating	(26)
Removr	Norway	2016	50	S-DAC	Operating	(93)
Climeworks	Iceland	2017	50	S-DAC	Operating	(26)
Climeworks	Switzerland	2017	900	S-DAC	Operating	(26)
Climeworks	Switzerland	2018	3	S-DAC	Operating	(26)
Removr	Norway	2018	50	S-DAC	Concept	(93)
Climeworks	Italy	2018	150	S-DAC	Operating	(26)
Climeworks	Switzerland	2018	600	S-DAC	Operating	(26)
Climeworks	Germany	2019	3	S-DAC	Operating	(26)
Climeworks	Netherlands	2019	3	S-DAC	Operating	(26)
Climeworks	Germany	2019	3	S-DAC	Operating	(26)
Climeworks	Germany	2019	50	S-DAC	Operating	(26)
Climeworks	Germany	2020	3	S-DAC	Operating	(26)
Removr	Norway	2020	50	S-DAC	Concept	(93)
Climeworks	Germany	2020	50	S-DAC	Operating	(26)
Sustaera		2021	0.365	S-DAC	Operating	(87)
Noya		2021	140	L-DAC	Operating	(87)
Global Thermostat	United States	2021	1000	S-DAC	Operating	(94)
Climeworks	Iceland	2021	4000	S-DAC	Operating	(95)
Removr	Norway	2022	50	S-DAC	Concept	(93)
Sustaera		2022	365	S-DAC	Operating	(87)

Heirloom		2022	462.5	Other	Operating	(87)
Carbon Collect	United States	2022	36500	S-DAC	Operating	Reuters
Prometheus	United States	2023	4450	S-DAC	Under construction	(96)
Removr	Norway	2024	300	S-DAC	Under construction	(93)
HIF Global	Chile	2024	600	Other	Under construction	HIF Global website
Carbyon	Netherlands	2024	1000	L-DAC	Under construction	Innovation Origins
Removr	Norway	2025	2,000	S-DAC	Concept	(93)
Climeworks	Iceland	2025	36000	S-DAC	Under construction	(95)
Carbon Engineering	United States	2025	500,000	L-DAC	Under construction	Carbon Engineering website
Carbon Engineering	Norway	2026	500,000	L-DAC	Concept	(97)
Carbon Engineering	Scotland	2026	1,000,000	L-DAC	Concept	(98)
Removr	Norway	2027	100,000	S-DAC	Concept	(93)
Climeworks	Norway	2029	184,000	S-DAC	Concept	(82)
Removr	Norway	2029	1,000,000	S-DAC	Concept	(93)
Project Cypress	United States	2029	1,000,000	S-DAC	Concept	(88)
Climeworks	Iceland	2030	1,000,000	S-DAC	Concept	(95)
Climeworks	United States	2030	1,000,000	S-DAC	Concept	(95)
Global Thermostat	United States	2030	1,000,000	S-DAC	Concept	(94)
Climeworks	United States	2030	1,000,000	S-DAC	Concept	(82)

Project Bison	United States	2030	5,000,000	S-DAC	Concept	(99)
Carbon Engineering	United States	2035	100,000,000	L-DAC	Concept	(100)

D. Technology Growth Projections

We apply the logistic substitution method (see Supplementary Note #3) to forecast feasible pathways for future DACCS adoption. The parameters required for this projection are: (1) initial capacity, (2) growth rate, and (3) saturation level (or market pull). Our baseline initial capacity, which we use for the pathways for the DACCS feasibility space modeled in GCAM, is the capacity of announced plants that are targeted to begin operation by 2035 (see Section C and Table S1). We use growth rates from historical analogs, which we obtain by fitting the closed form logistic equation to capacity data for each analog (see Supplementary Note #4 for an overview of the approach, Section B and Figure S1 for the results of the empirical fits, and Section F for our sensitivity analysis). For the saturation level, we use the modeled DACCS capacity in 2100 in a GCAM climate policy scenario constrained only by our emissions pathway (see Materials and Methods). This section describes the selection of the parameters for the logistic substitution model in more detail.

First, we determine our initial DAC capacity value. Future capacity for early-stage technologies is highly uncertain; while there has been a large amount of investment and interest in DAC, with ambitious market projections, it remains to be seen whether capacity will meet, fall short of, or exceed these expectations. To capture this uncertainty, we use three different approaches to select initial capacity. Our baseline scenarios use all proposed DAC capacity planned to come online by 2035. We examine the sensitivity of our projections to two lower capacity estimates: current operational capacity (a lower bound) and capacity under construction (and slated to come online by 2025, a more conservative estimate). These lower initial capacity values result in lower projected capacity, especially for higher growth scenarios (see Figure 3b and Table S2 and Figure S5). However, given that some of our analogs have very low growth rates, the feasibility space that we calculate using the more ambitious early capacity estimates captures the lower end of this uncertainty space well. It is also possible that capacity in 2035 could exceed current announcements, leading to a higher upper bound in 2050 and an earlier saturation at the market pull level (currently 2074 for the offshore wind analog).

Second, we use historical technology analogs to select a range of growth rates for projecting DACCS adoption over time. These analogs and the analog selection process are described in Section B. We fit historical capacity data to the logistic growth model (see Section B and Materials and Methods for more description and the resulting growth parameters and Figure S1 for plots of the analog capacity data). The logistic fit for all selected analogs performs well ($R^2 >$ 0.95). However, we note that growth rate estimates may change as more data become available, particularly for technologies that have not yet reached their inflection points (see Supplementary Section F). Additionally, how future DACCS growth rates will compare to growth rates observed for historical analogs is a large source of uncertainty for projecting future

DACCS adoption. As with other literature describing feasibility spaces for early-stage technologies, this uncertainty can point to important policy levers for accelerating DACCS growth. For example, previous research has focused on the drivers of fast growth in solar PV and whether these conditions could be replicated for other technologies (101).

Third, we select an exogenous saturation level to represent the market pull for DACCS. Previous work has largely focused on early-stage technologies that have a defined addressable market (e.g., demand for new energy technologies (31, 34)). For technologies without a clear market, the saturation level should represent a reasonable constraint on the market (22). However, for DACCS, there is no pre-existing market, and the primary service that DACCS provides is CO_2 removal (in contrast to some other CDR technologies, such as BECCS, which provides both energy and CO_2 removal services). For DACCS, we use the 15.9 $GtCO_2$ DACCS demand in 2100 under our climate policy scenario (i.e., a lower overshoot 1.5°C emissions budget) with other default GCAM inputs (102). We interpret this value as the market demand for DACCS under climate policy. We note that our scenarios project levels of CDR on the high end of scenarios in the AR6 database (66), which we argue is appropriate for representing potential market pull and thus capturing the full feasibility space. Technological innovation, for example in difficult to decarbonize sectors, may reduce the market pull for DACCS.

Table S2: *Reference early capacity choices for DACCS projections.*

Plant status used for initial condition	**Capacity ($MtCO_2$)**	**Year of *t* = 0**
Operational	0.046	2023
Under construction	0.588	2025
Announced	113.374	2035

E. Additional Adoption and Innovation Indicators

Beyond operating, under construction, and announced capacity, there are a variety of indicators that can be used to measure innovation for early-stage technologies (see Figure S3).

Advanced market commitments (AMCs), where government or corporate buyers guarantee the purchase of a product, and thereby de-risk and reduce the costs of developing that product, may be important indicators of sales that have a higher likelihood of being delivered (103). AMCs have been an important early tool for early DAC innovation. For example, Frontier has made an initial AMC to buy $1 billion in carbon removal by 2030 (104) and facilitated purchases of 2,246 tonnes of CO_2 removal from four start-ups: Carbon to Stone, AspiraDAC, Calcite-Origen, and RepAir. Other public purchases include 400 $ktCO_2$ by Airbus from 1PointFive, 315 $ktCO_2$ by Microsoft from Heirloom, and 250 $ktCO_2$ by Amazon from 1PointFive. Purchase agreements aggregated by CDR.fyi include Frontier and Airbus, as well as Shopify (21,845 tCO_2), Stripe (1,638 tCO_2), and 65 other purchasers. Purchases facilitated by supply side marketplaces include Climeworks partners Carbon Removed (8.7 tCO_2), Klimate (44.3

tCO_2), and Watershed (137 tCO_2). We source data on purchase agreements from cdr.fyi (85) (accessed September 12, 2023) and Google searches. Purchases total 1,155,704 tCO_2 (see Table S3).

Additionally, start-ups with highly competitive public grants indicate potentially transformative but high-risk technologies (105); however, when start-ups also receive private sector investments, they reflect to some extent that, despite risks, a particular solution can potentially deliver financial returns within a shorter time frame (106–109). To reflect these investments, we sourced data on DAC investments from the proprietary i3 database (86) (accessed January 19, 2022) that records investments from public and private sources and supplemented it with additional data. Within the i3 investment database, we searched for 13 key tokens such as “direct air capture,” “scrubbers”, or “carbon sequestration” to identify DAC companies. We then individually analyzed companies with descriptions containing these tokens to categorize what technology they are developing: solid sorbent, liquid solvent, or other. We only included companies with investment records (i.e., amounts and dates) and used Crunchbase (110) to complete missing investment information in i3. Some of these investments are purchases of credits for carbon removal, such as by Shopify, and were also included in our analysis.

We present trends in start-up funding and AMCs for DAC in Figure S3. Note that this figure does not include the recently-announced $3.5 billion allocated by the U.S. DOE to develop regional DAC hubs; as of August 11, 2023, two hub locations have been selected for award negotiations, but funds have not been disbursed (111). Beyond these hubs, funds have also been allocated to pilot or design projects (88). These government initiatives provide further indication that DAC proposals by start-ups may receive the resources required to be built. Both public and private investments and AMCs are used by early-stage companies to scale up their capture technology and reduce costs. However, some companies receiving grants or private investments are at an earlier stage than the companies receiving AMCs and feature novel DAC technologies such as membrane separation or moisture swing. The type of investment therefore may be a partial indicator of the maturity of a technology and potential for near-term growth.

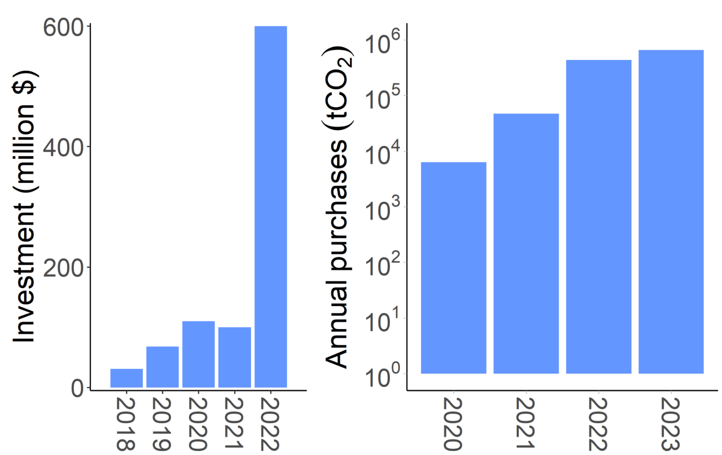

Figure S3: *Investments (left) and purchase agreements (right) with DAC companies.*

Table S3: *Carbon credit purchases from DACCS start-ups*

Supplier	Date announced	Quantity ($t\ CO_2$)	Purchaser
1PointFive	9/12/2023	250,000	Amazon
Heirloom	9/7/2023	315,000	Microsoft
Airhive	9/7/2023	943	Frontier
Spiritus	9/7/2023	713	Frontier
Holocene	9/7/2023	332	Frontier
Carbon Atlantis	9/7/2023	275	Frontier
Arbon	9/7/2023	173	Frontier
Carbon Engineering	8/18/2023	1	Howells Associates
1PointFive	8/1/2023	10,000	All Nippon Airways
1PointFive	8/1/2023	10,000	All Nippon Airways
1PointFive	8/1/2023	10,000	All Nippon Airways
Carbon Engineering	7/27/2023	4	Apheris AI
Carbon Engineering	7/11/2023	1	Kirk & Co
Climeworks	6/30/2023	35	Aggregate Purchase
Noya	6/22/2023	33	Aggregate Purchase
Carbon Capture	6/21/2023	40,000	BCG
Carbon Engineering	6/21/2023	5	FundApps Ltd
Carbon Engineering	6/19/2023	7	The Craftory Limited
Carbon Engineering	6/15/2023	21	Phoenix Court Group Limited
Carbon Engineering	6/9/2023	1	Ghyston Limited
Climeworks	5/23/2023	25,000	JPMorgan Chase
Carbon Engineering	5/14/2023	5	GSPV Limited

Climeworks	5/1/2023	35	Aggregate Purchase
1PointFive	4/26/2023	0	NextGen
Carbon Engineering	4/20/2023	2	Bennetts Associates
Carbon Engineering	3/31/2023	5	Bennetts Associates
Carbon Engineering	3/27/2023	1	Trafalgar House Penseions Administration Limited
Carbon Engineering	3/27/2023	1	Faculty Science
Climeworks	3/21/2023	15	Aggregate Purchase
Carbon Engineering	3/21/2023	1	Lawton Communications Group
Carbon Engineering	3/20/2023	1	Lightspeed X Visionaries Club
Carbon Capture	3/16/2023	280	Carbonx Climate
Carbon Engineering	3/13/2023	17	Plural UK Management Limited
1PointFive	3/8/2023	0	Houston Astros
Carbon Engineering	3/1/2023	10	Plural UK Management Limited
Heirloom	1/30/2023	2	WRLD Foundation
Heirloom	12/1/2022	6	WRLD Foundation
Carbon Engineering	11/25/2022	95	Softwire
Carbon Engineering	11/25/2022	95	Softwire Employees
Carbon Engineering	11/16/2022	2	Tech Nation Group
Climeworks	11/14/2022	10,000	H&M Group
Climeworks	10/12/2022	10	Aggregate Purchase
Carbon Engineering	9/28/2022	2	Synthesis Capital

Carbon Engineering	8/31/2022	1	Howtospeakwhale
Carbon Engineering	8/31/2022	1	Individual
Climeworks	8/30/2022	10,000	UBS Financial
Cedar Carbon	8/19/2022	1	Individual
Heirloom	8/9/2022	0	Microsoft
Climeworks	7/13/2022	10,000	Microsoft
Climeworks	7/11/2022	1	Aggregate Purchase
Heirloom	7/6/2022	49	Klarna
Carbon Engineering	6/30/2022	6	Oxwash
AspiraDAC	6/29/2022	500	Frontier
Calcite-Origen	6/29/2022	278	Frontier
RepAir	6/29/2022	199	Frontier
Climeworks	6/21/2022	1	Aggregate Purchase
Sustaera	6/9/2022	80	Aggregate Purchase
Sustaera	6/2/2022	165	Aggregate Purchase
Climeworks	6/2/2022	5	Aggregate Purchase
Carbon Engineering	5/23/2022	12	What3words
Heirloom	5/20/2022	1	Terraset
Climeworks	5/13/2022	1	Aggregate Purchase
Climeworks	5/3/2022	0	Boom
Climeworks	4/22/2022	0	Aggregate Purchase
Sustaera	4/7/2022	80	Aledade
Heirloom	4/7/2022	30	Aledade
Noya	4/7/2022	27	Aledade
Climeworks	4/6/2022	0	Verdane

Carbon Engineering	4/4/2022	31	Senderwood
Climeworks	4/1/2022	5	Aggregate Purchase
Carbon Engineering	3/31/2022	5	Aggregate Purchase
Carbon Engineering	3/31/2022	5	Supercritical
Climeworks	3/30/2022	0	Swarowski
Carbon Engineering	3/29/2022	22	Thirdfort
Sustaera	3/28/2022	5,000	Shopify
Noya	3/28/2022	1,445	Shopify
Carbon Engineering	3/24/2022	59	Softwire
Carbon Engineering	3/23/2022	20	accuRx
1PointFive	3/17/2022	400,000	Airbus
Carbon Engineering	3/15/2022	2	Howells Associates
Climeworks	3/11/2022	0	Aggregate Purchase
Climeworks	3/3/2022	290	Zendesk
Carbon Engineering	3/1/2022	16	Space Ape Games
Carbon Engineering	2/28/2022	94	Infogrid
Carbon Engineering	2/28/2022	94	Information Grid
Climeworks	2/22/2022	5	Aggregate Purchase
Climeworks	2/15/2022	0	Aggregate Purchase
Climeworks	2/11/2022	3	Aggregate Purchase
Mission Zero	2/11/2022	0	Chan Zuckerberg Initiative (CZI)
Climeworks	2/9/2022	0	Rothesay Life
Mission Zero	2/7/2022	358	Aggregate Purchase
Climeworks	1/11/2022	0	Aggregate Purchase
Climeworks	12/27/2021	1	Aggregate Purchase

Carbon Engineering	12/23/2021	1	Apheris AI
Aggregate Supplier (Marketplace Report)	12/22/2021	4	Aggregate Purchase
Carbon Engineering	12/22/2021	2	Searchpilot
Carbon Engineering	12/21/2021	6	PPC Protect
Climeworks	12/20/2021	9,000	LGT
Sustaera	12/14/2021	714	Stripe
Climeworks	12/9/2021	0	BCG
Carbon Engineering	12/8/2021	8	Hey Habito
Climeworks	12/1/2021	2	WRLD Foundation
Heirloom	12/1/2021	1	WRLD Foundation
Climeworks	11/30/2021	2,000	Block
Carbon Engineering	11/30/2021	1,000	BMO Financial Group
Carbon Engineering	11/30/2021	4	Satellite Vu
Climeworks	11/22/2021	0	Aggregate Purchase
Climeworks	11/16/2021	0	Ocado Retail
Climeworks	11/1/2021	500	Aggregate Purchase
Climeworks	11/1/2021	500	Aggregate Purchase
Climeworks	11/1/2021	400	Aggregate Purchase
Climeworks	11/1/2021	300	Aggregate Purchase
Climeworks	11/1/2021	200	Aggregate Purchase
Climeworks	11/1/2021	100	Aggregate Purchase
Climeworks	10/25/2021	2	Aggregate Purchase
Heirloom	10/20/2021	73	Klarna
Climeworks	10/20/2021	72	Klarna
Climeworks	10/14/2021	0	Coldplay

Climeworks	10/13/2021	0	Aggregate Purchase
Climeworks	9/29/2021	2	Aggregate Purchase
Climeworks	9/10/2021	7	Aggregate Purchase
Heirloom	9/9/2021	400	Shopify
Carbon Engineering	9/9/2021	9	Infogrid
Carbon Engineering	9/9/2021	9	Information Grid
Climeworks	9/8/2021	0	Aggregate Purchase
Carbon Engineering	8/26/2021	9	accuRx
Climeworks	8/25/2021	20,000	Swiss Re
Climeworks	8/16/2021	0	Aggregate Purchase
Climeworks	7/7/2021	0	Aggregate Purchase
Climeworks	7/6/2021	0	Aggregate Purchase
Climeworks	6/23/2021	0	The Economist Group
Climeworks	6/21/2021	1	Aggregate Purchase
Climeworks	6/4/2021	4	Aggregate Purchase
Mission Zero	5/27/2021	358	Stripe
Heirloom	5/27/2021	244	Stripe
Climeworks	5/10/2021	0	Aggregate Purchase
Climeworks	4/7/2021	0	Aggregate Purchase
Heirloom	3/30/2021	5	Sourceful
Carbon Engineering	3/9/2021	10,000	Shopify
Climeworks	3/5/2021	0	Aggregate Purchase
Climeworks	3/5/2021	0	Aggregate Purchase
Climeworks	1/11/2021	1	Aggregate Purchase
Climeworks	1/1/2021	1,400	Microsoft

Climeworks	12/7/2020	0	Aggregate Purchase
Climeworks	11/9/2020	0	Aggregate Purchase
Climeworks	10/7/2020	0	Aggregate Purchase
Climeworks	9/15/2020	5,000	Shopify
Climeworks	9/10/2020	1,000	Audi
Climeworks	9/7/2020	0	Aggregate Purchase
Climeworks	8/7/2020	0	Aggregate Purchase
Climeworks	7/7/2020	0	Aggregate Purchase
Climeworks	5/18/2020	322	Stripe
Carbon Engineering	No date	20	Thermo Fisher
Noya	No date	1	Piva Capital
Heirloom	No date	1	Piva Capital
Heirloom	No date	0	Verdane

F. Sensitivity Analysis

There are four key design choices in projecting future growth in novel technologies such as DACCS, each of which represents a distinct source of uncertainty in defining the feasibility space. The first choice involves selecting the functional form for representing growth over time. For the logistic substitution model (which we use in our analysis), each of the three input parameters is also a design choice and is subject to various uncertainties:

- The growth rate k, which is determined using a logistic fit to historical technology analogs, is sensitive to the choice of analogs and the underlying capacity data.
- The initial capacity C_0, which is determined using early announcements of DACCS capacity, is sensitive to uncertainty in whether announced capacity will be realized.
- The saturation level L, which is determined by the market for DACCS in GCAM, is sensitive to the choice of IAM and scenario design and input parameters.

This section examines the sensitivity of our calculated feasibility space for DACCS to each of these input parameters. We also compare the feasibility space for DACCS calculated using the logistic substitution model with another model (the Gompertz model (17, 37)).

Sensitivity to growth rate

The logistic growth rates calculated for historical technology analogs are subject to various uncertainties. Early capacity data can be a source of uncertainty for at least two reasons: (1) for some technologies, particularly ones that have existed for many years, early adoption data can be missing and (2) there can be some ambiguity in when the formative phase begins and thus when to start the data series (see Supplementary Note #2 for discussion of the formative phase). To explore these potential sources of uncertainty, we simulate a case where we add up to 20 years of synthetic data to each capacity data series, where the data points are all randomly generated to be equal to or less than the first capacity data point. We repeat the simulation 100 times. The resulting growth rates can vary by up to approximately 30%, with the majority of growth rates varying by less than 1% (see Figure S4a). The technologies with the highest relative change have moderate to low growth rates and shorter time-series data (e.g., aluminum refining with *k* varying from 5-50% and motor gasoline with *k* varying from -50 to +30%). As a result, adding early data to the capacity time series generally has a minimal effect on the calculation of the feasibility space for DACCS.

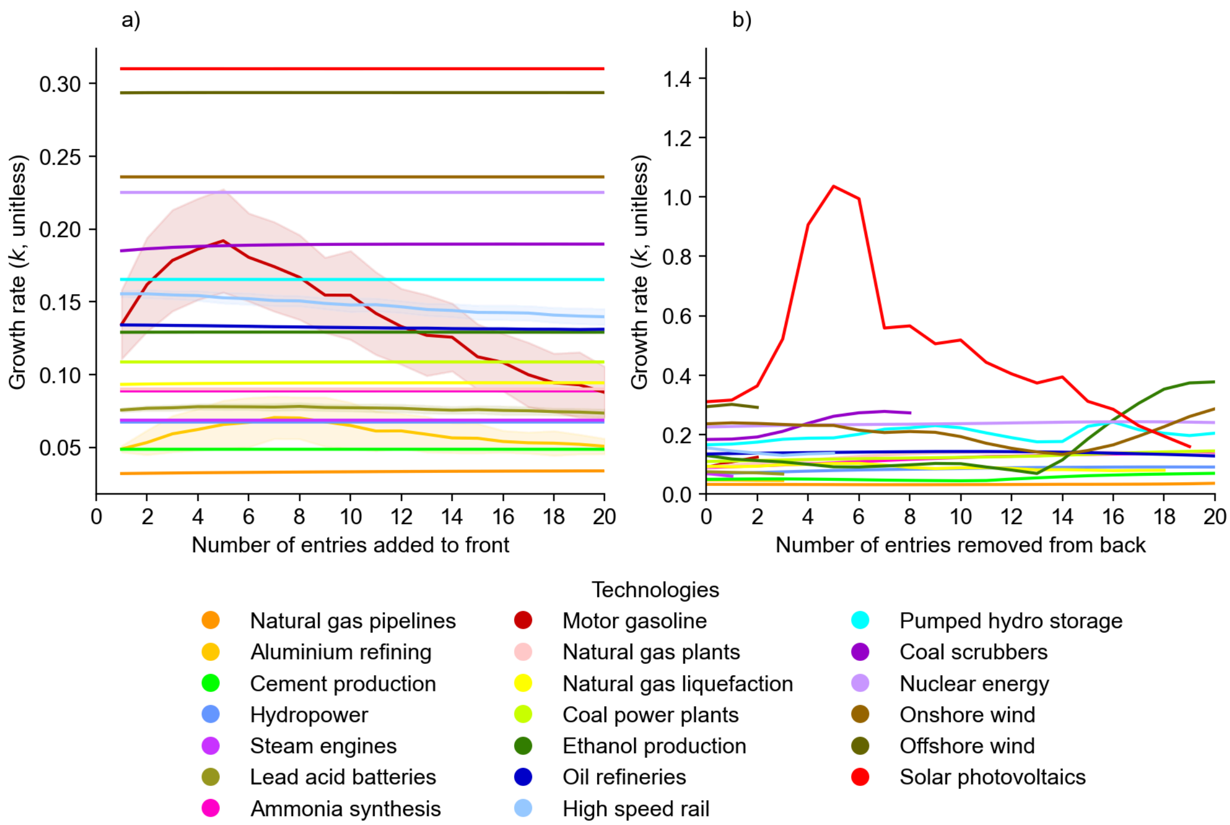

Figure S4. *Estimated logistic growth rates for technology analogs for DACCS where (a) up to 20 years of synthetic data were added to the beginning of the time series and (b) up to 20 years of recent data were removed from the time series. Shading shows the results for k* values *across 100 simulations (see text for details on methods).*

Recent capacity data can also be a source of uncertainty in calculation of *k* for at least two reasons: (1) some datasets are not updated and do not contain more recent capacity data and

(2) capacity data for the future is inherently not available. To explore these potential sources of uncertainty, we simulate a case where we remove up to 20 years of data from the end of each capacity data series. For data series where removing 20 data points would result in a data series that is shorter than 20 points total (and thus would not pass our data quality filters, see Section B), we only remove the number of data points that leaves at least 20 data points in the remaining dataset (see Figure S4b). Unlike with early adoption data, the value of k can be highly sensitive to recent and pivotal information for rapidly advancing technologies. Specifically, for solar PV, the value of k can change by up to 300% (k = 1.1 when excluding the last 5 years of data). For other technology analogs, variation in k ranges from 1-30% when excluding the last 5 years of data and 5-400% when excluding up to 20 years of data. The largest changes in k in absolute terms are observed for coal scrubbers (0.18 to 0.29), and ethanol production (0.1 to 0.4). These sensitivities suggest that variation in k is reasonable across short time frames but that k could change substantially over longer time frames.

Sensitivity to initial capacity

Future deployment of DAC plants over the next 5-10 years, which is used to determine the initial capacity C_0 in the logistic substitution model, is also uncertain. We discuss three possible approaches to determining initial capacity (see Supplementary Section C): currently operational DAC plants, DAC plants currently under construction, and plant construction announcements. Currently operational DAC plants, many of which are early pilot plants, represent a lower bound on the initial capacity value. Plants under construction are more certain than those that have only been announced but may still not be realized if there are unforeseen cost overruns or construction delays. Announced DAC plants may also not be built, particularly for cases where these announcements represent more aspirational goals for companies. We present uncertainty in future DAC capacity projections across our technology analogs using each of the definitions of C_0 described above (see Figure S5). While all the three conditions reach the same saturation level, higher initial values lead to faster saturation (by ~25 years for high growth analogs) compared to the lowest initial value. Additionally, we note that initial capacity may be higher than the levels considered here if plants that have not yet been announced are built.

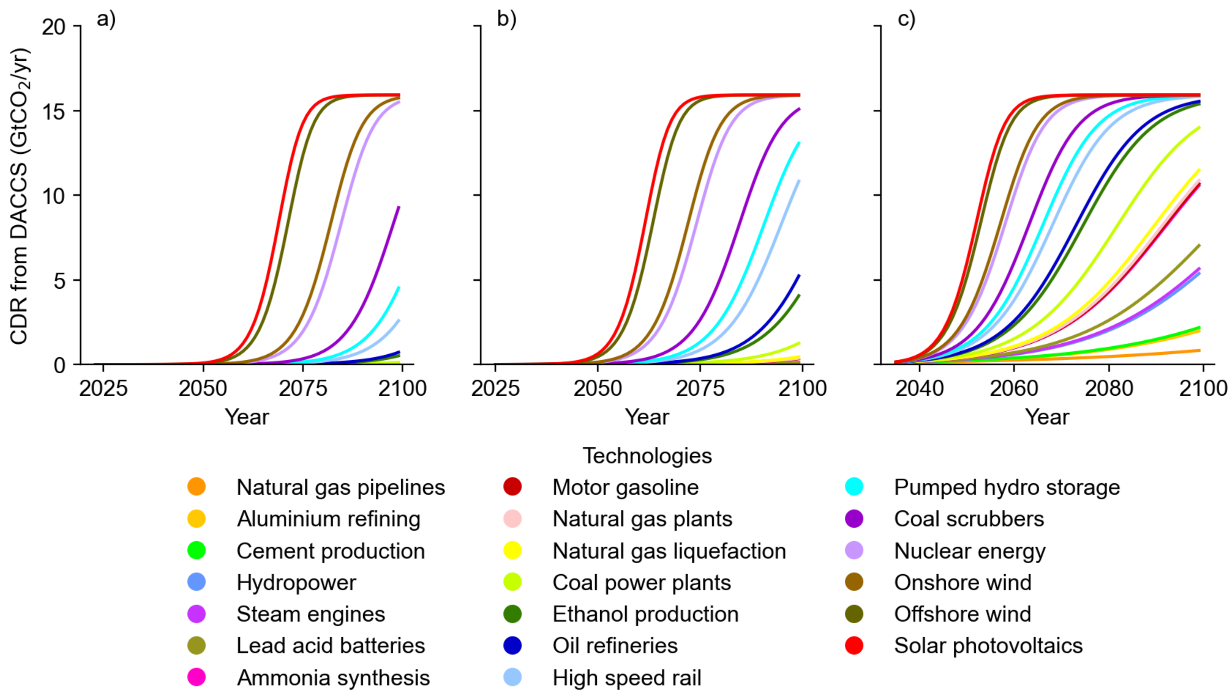

Figure S5. *DACCS growth estimates with varied initial conditions for early DAC capacity (see Section C): (a) operational DAC plants (0.046 Mt CO_2/yr), (b) plants under construction (0.588 Mt CO_2/yr), and (c) plant announcements (113.374 Mt CO_2/yr).*

Sensitivity to market demand

Future market demand pull for DACCS depends on many factors. Because DACCS (and other CDR technologies) often serves as a backstop technology, the availability and attractiveness of other emissions reduction technologies can substantially change the demand for DACCS, as can competition with other CDR technologies (see Supplementary Note #6). We use annual DACCS demand in GCAM in 2100 (15.9 $GtCO_2$) under a scenario with our policy constraint (to meet a 1.5°C temperature target) as our estimate of the market demand pull. However, modeled CDR from DACCS varies across IAMs, with GCAM on the high end of the range of AR6 scenarios. Among the IAM scenarios in AR6 that include DACCS (which represent 31% of all scenarios), the level of DACCS in GCAM in 2100 is in the 96th percentile. The maximum value is 18.9 $GtCO_2$, and the 50th and 75th percentiles are 5.8 $GtCO_2$ and 10.3 $GtCO_2$. Other possible approaches to calculating market demand for DACCS include physical constraints like available storage or residual fossil fuels emissions. We model DACCS adoption using each of our technology analogs for each of these three potential definitions of *L* (see Figure S6).

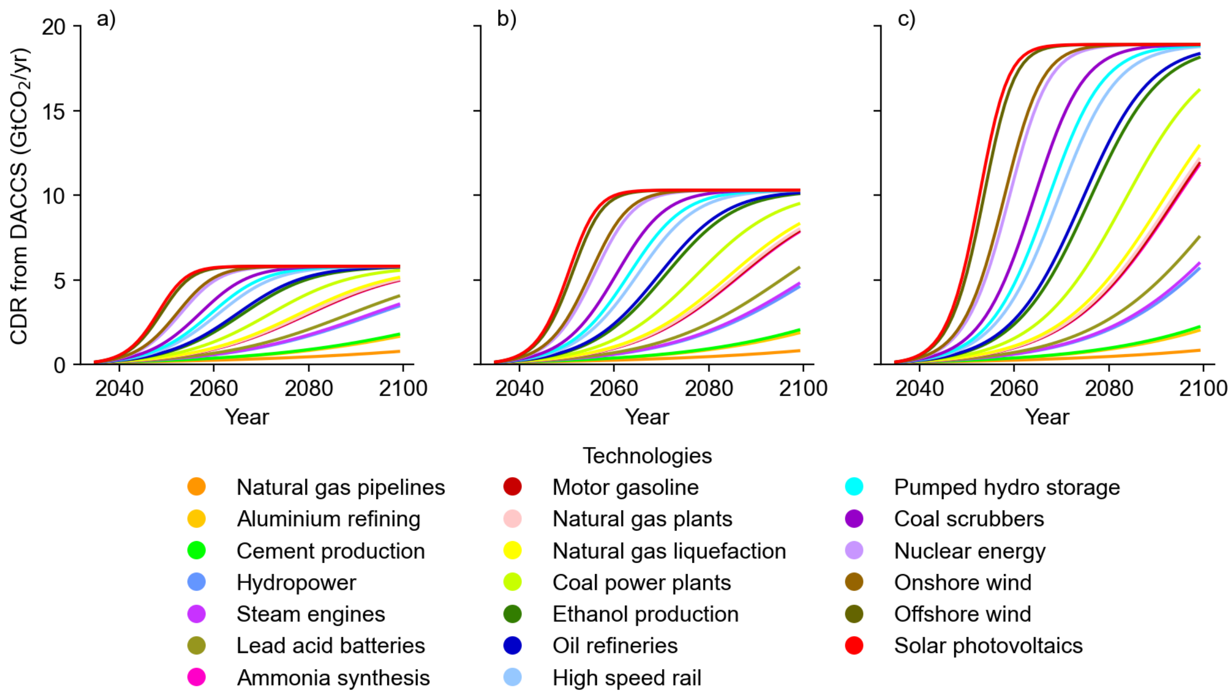

Figure S6. *DACCS growth estimates with varied saturation levels (see Section D): (a) 50th percentile (5.8 $GtCO_2$), (b) 75th percentile (10.3 $GtCO_2$), and maximum value (18.9 $GtCO_2$) in the AR6 database.*

Sensitivity to functional form

We also test an alternative to the logistic growth model, the Gompertz model (17, 37). Unlike the logistic growth model, the Gompertz model is not symmetrically distributed around the inflection year. Annual adoption is skewed to the right, resulting in a slower approach to the saturation level. The closed-form of the Gompertz model describes capacity C as a function of time t. Model parameters are the saturation level L, inflection year t_0, and growth rate c (which is different from logistic k):

$$C(t) = Le^{-e^{-c(t-t_0)}}. \quad \text{S5}$$

This is the solution to the differential equation:

$$\frac{dC(t)}{dt} = c\,C(t)\,ln\left(\frac{L}{C(t)}\right). \quad \text{S6}$$

As with the logistic substitution model, this equation can be discretizing for small time steps:

$$C_{t+1} = C_t + c\,C_t\,ln\left(\frac{L}{C_t}\right). \quad \text{S7}$$

We repeat the same steps with the Gompertz model as the logistic substitution model, fitting the historical analogs to the closed-form Gompertz equation, extracting the growth parameter *c*, imposing the exogenous saturation (or market pull) level, and iteratively calculating future capacity from the three different initial conditions. Figures S1-S2 compare the fits across historical analogs, and Figure S7 compares the resulting projections for DACCS growth over time. Some technologies show faster growth using the Gompertz model, while others show slower growth; however, the feasibility space across the two models is similar.

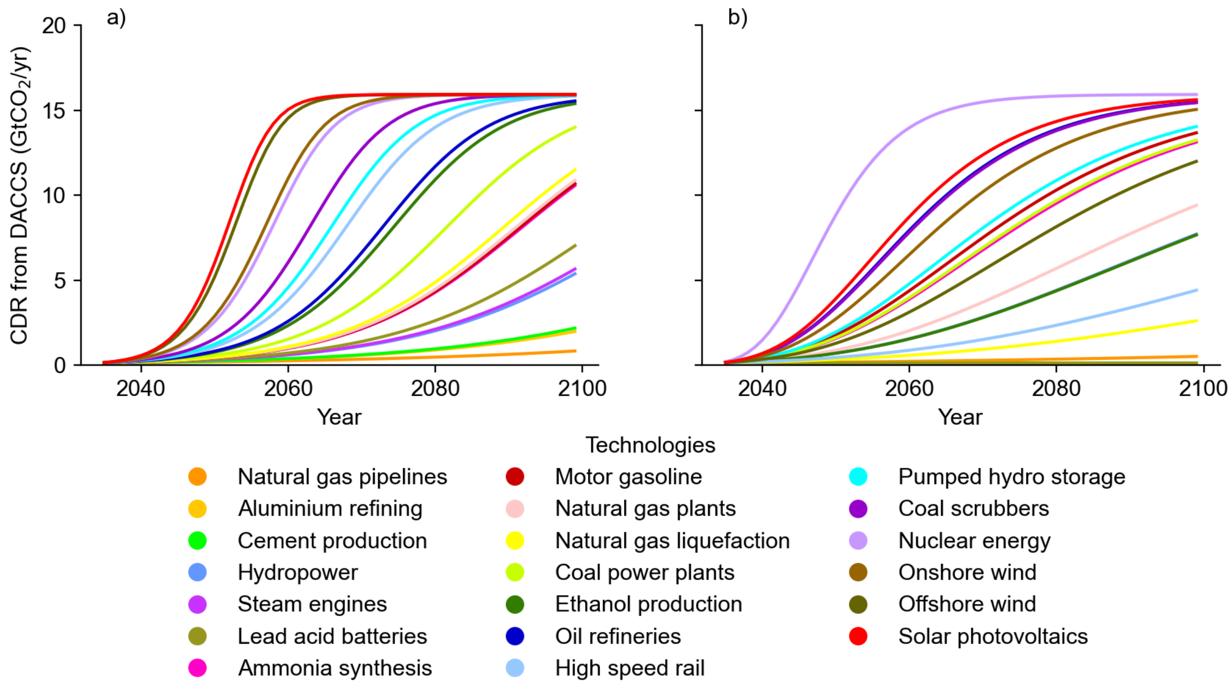

Figure S7: *Comparison of DACCS projections using (a) logistic and (b) Gompertz models.*

G. Supplementary Figures

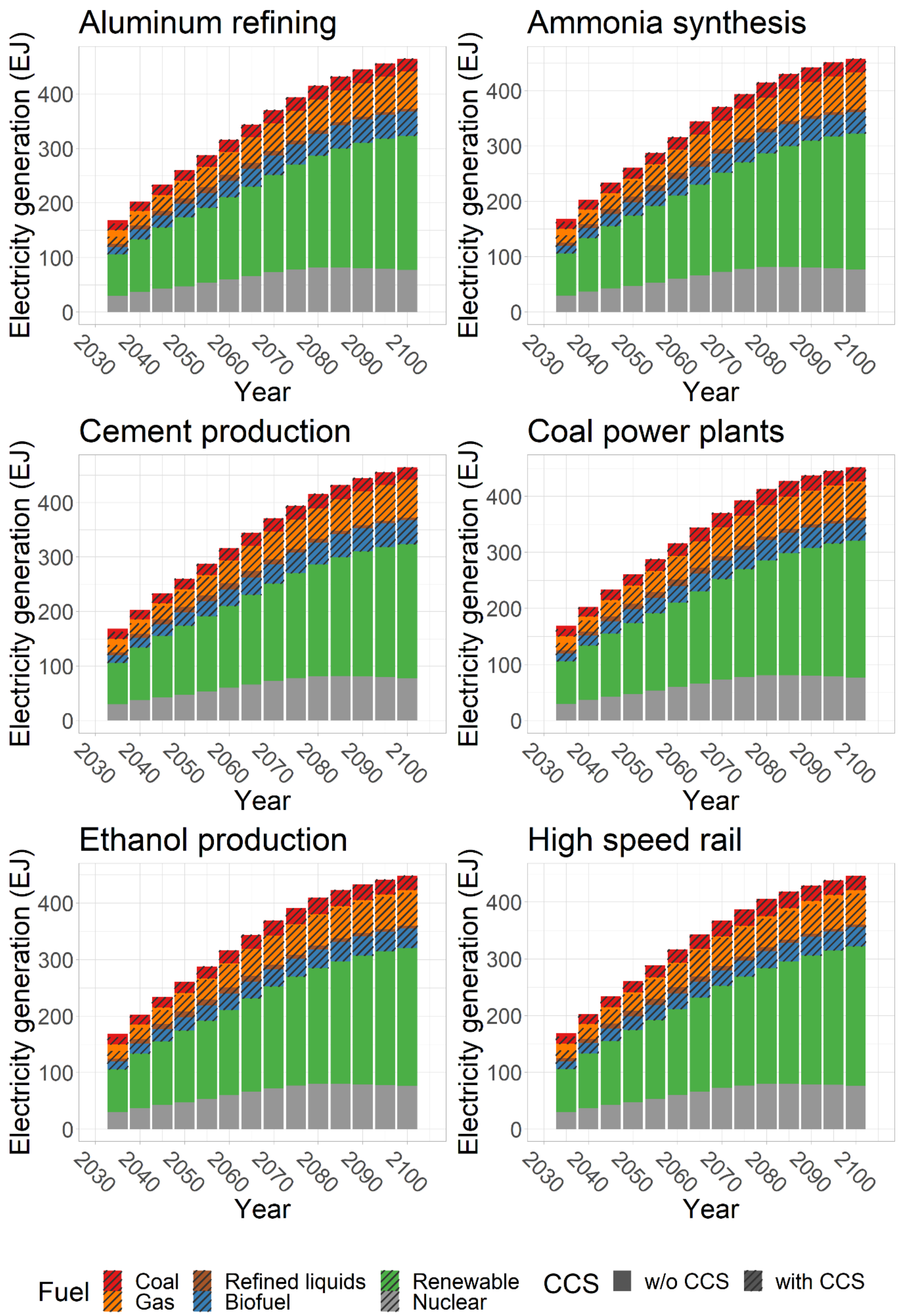

Figure S8: *Electricity generation by fuel source for the DACCS adoption pathways based on six analogs: aluminum refining, ammonia synthesis, cement production, coal power plants, ethanol production, and high speed rail.*

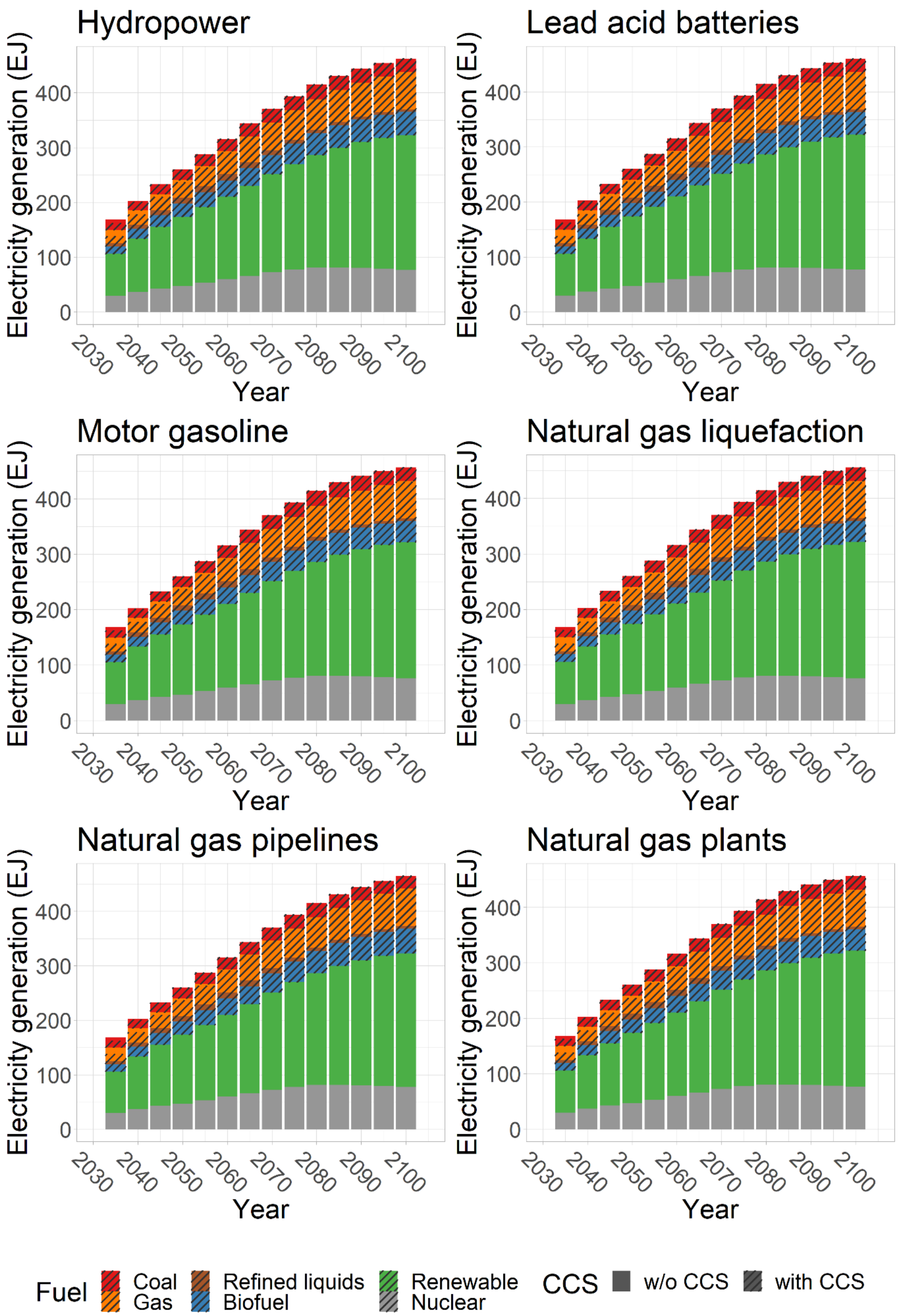

Figure S9: *Electricity generation by fuel source for the DACCS adoption pathways based on six engineering and infrastructure analogs: hydropower, lead acid batteries, motor gasoline, natural gas liquefaction, natural gas pipelines, and natural gas plants.*

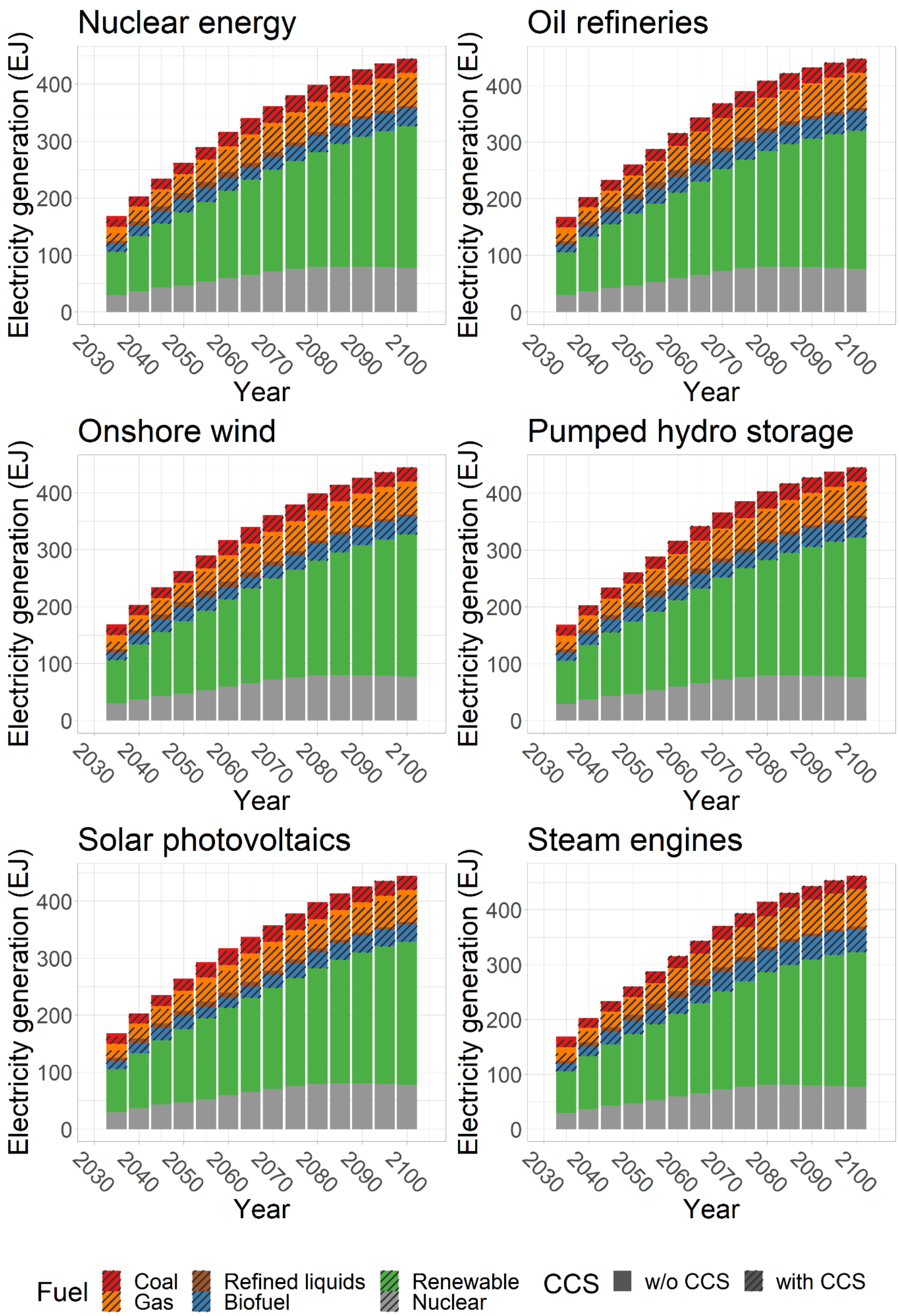

Figure S10: *Electricity generation by fuel source for the DACCS adoption pathways based on six analogs: nuclear energy, oil refineries, onshore wind, pumped hydro storage, solar photovoltaics, steam engines.*

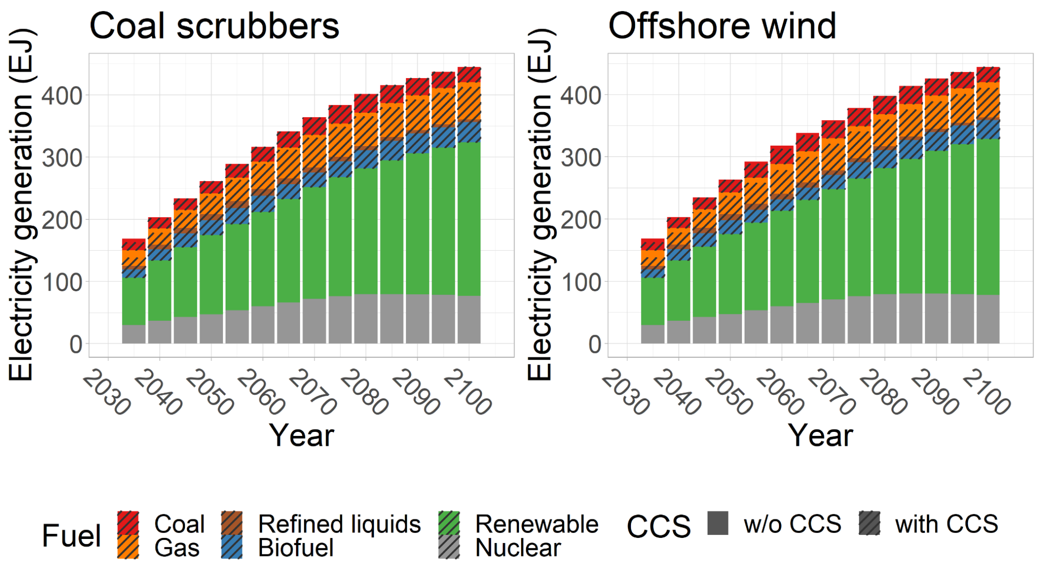

Figure S11: *Electricity generation by fuel source for the three DACCS adoption pathways based on the three mitigation analogs, and an unconstrained DACCS adoption scenario using SSP2 (middle-of-the-road) cost assumptions*

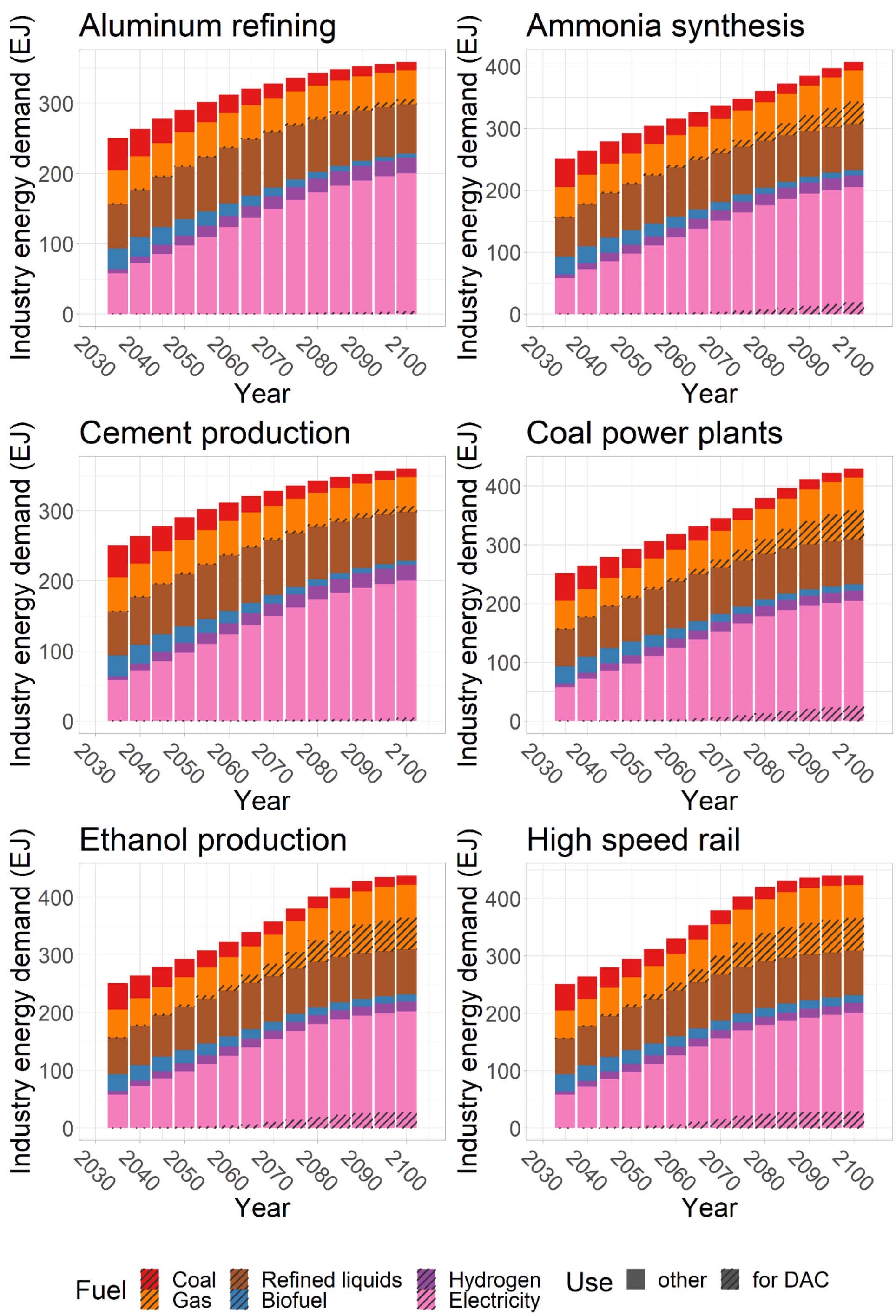

Figure S12: *Final industry energy demand by fuel source for the DACCS adoption pathways based on six analogs: aluminum refining, ammonia synthesis, cement production, coal power plants, ethanol production, and high speed rail.*

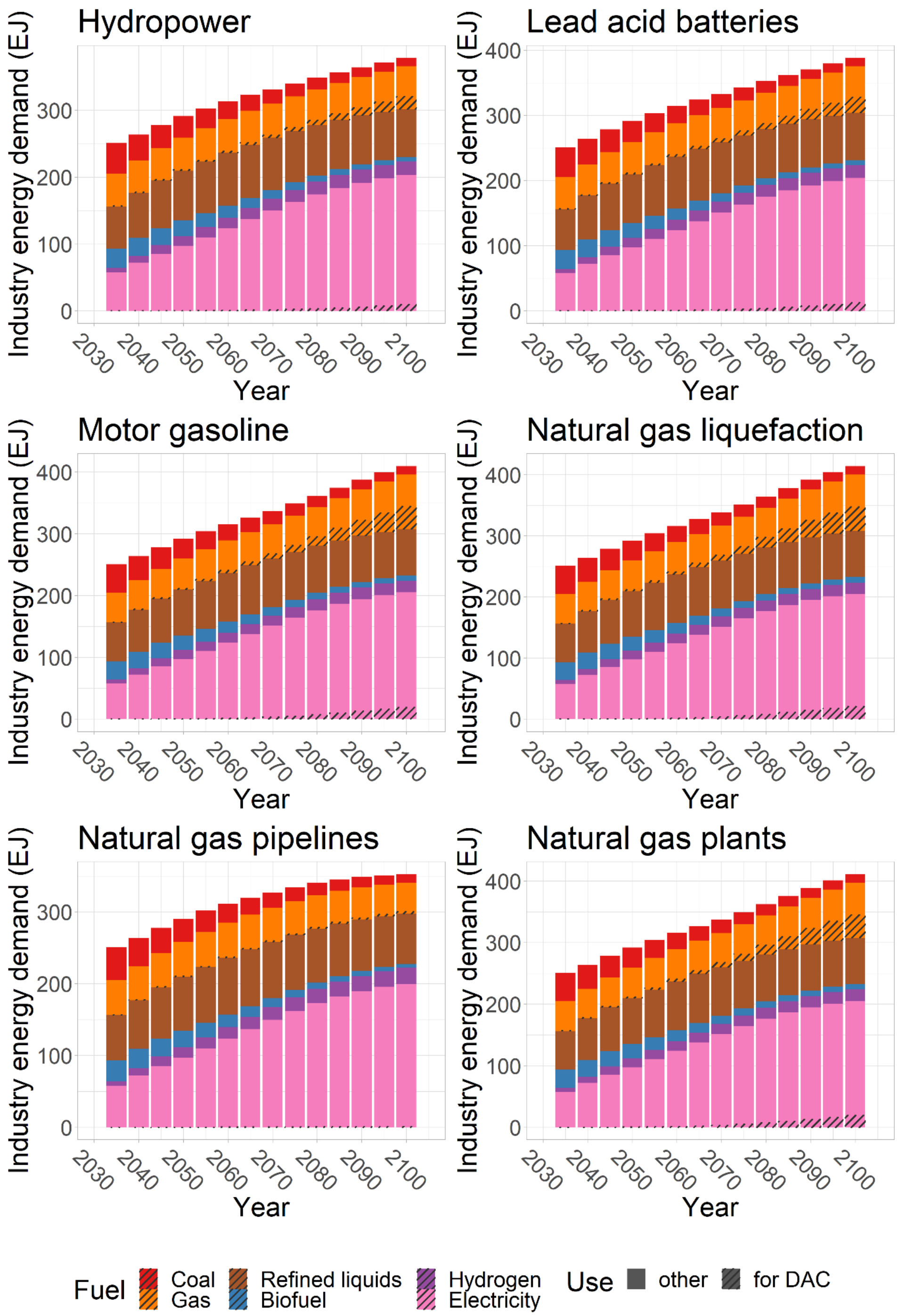

Figure S13: *Final industry energy demand by fuel source for the DACCS adoption pathways based on six engineering and infrastructure analogs: hydropower, lead acid batteries, motor gasoline, natural gas liquefaction, natural gas pipelines, and natural gas plants.*

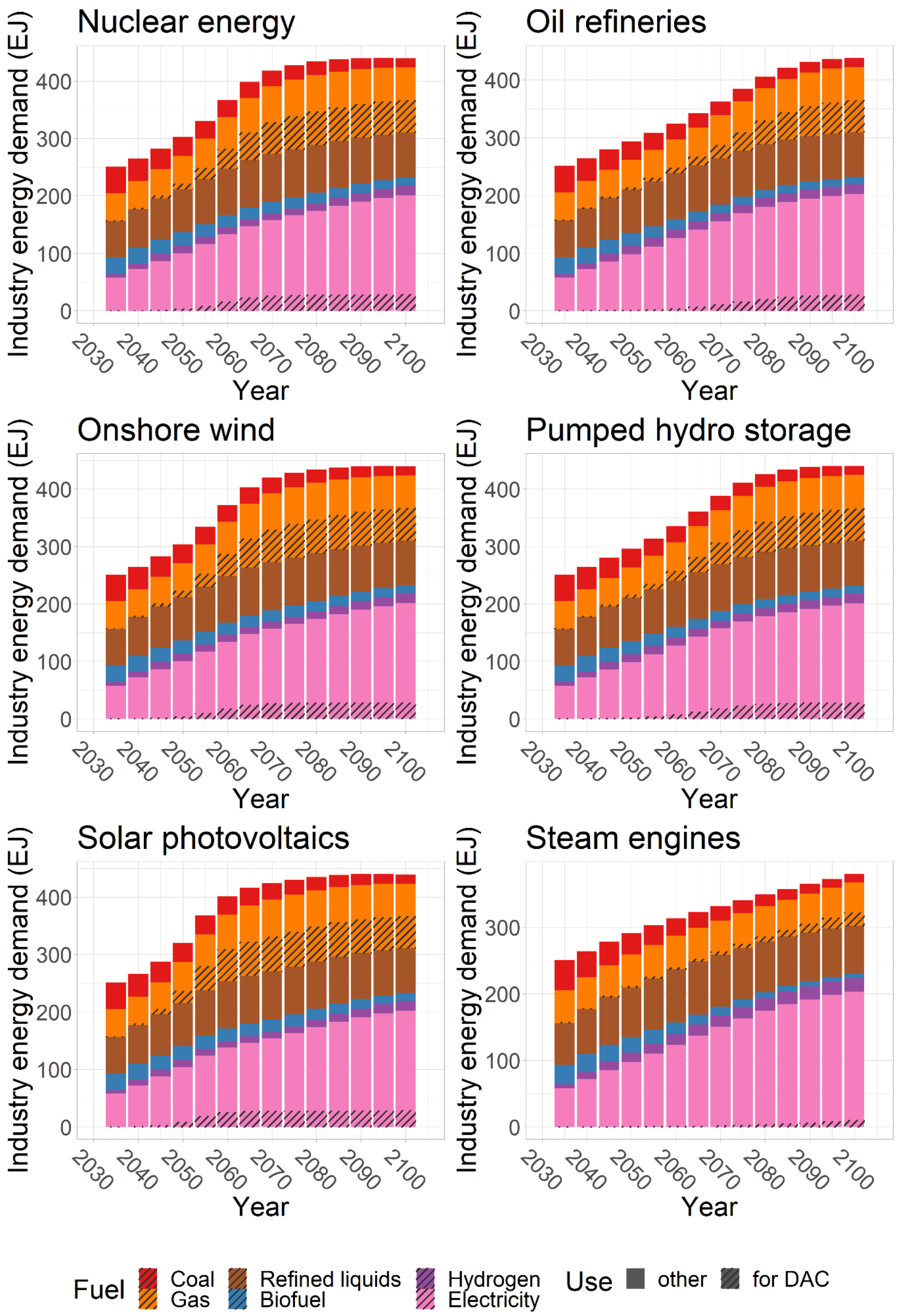

__Figure S14:__ Final industry energy demand by fuel source for the DACCS adoption pathways based on six analogs: nuclear energy, oil refineries, onshore wind, pumped hydro storage, solar photovoltaics, steam engines.

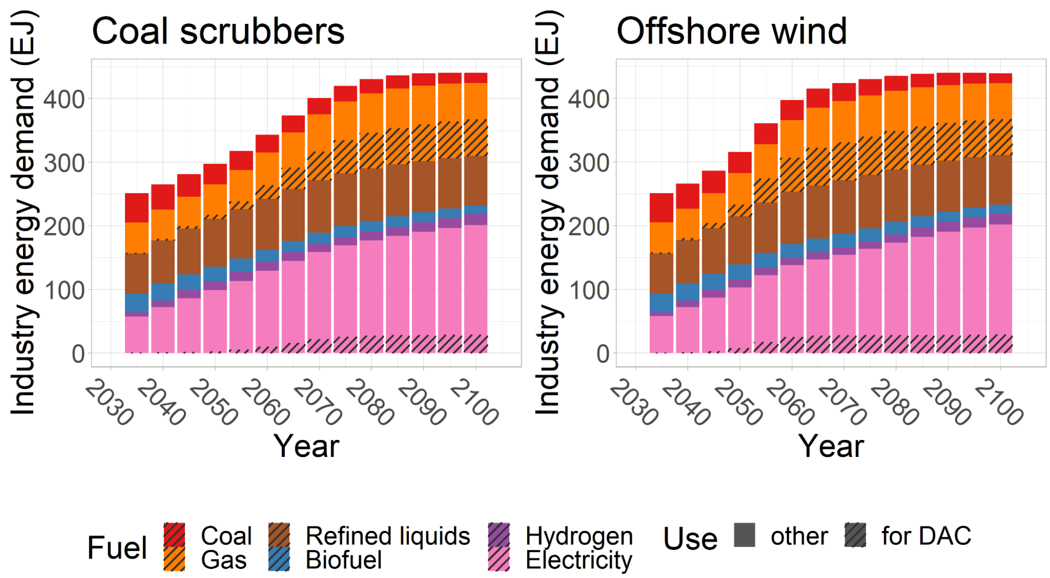

Figure S15: *Final industry energy demand by fuel source for the two DACCS adoption pathways based on two analogs: coal scrubbers and offshore wind.*

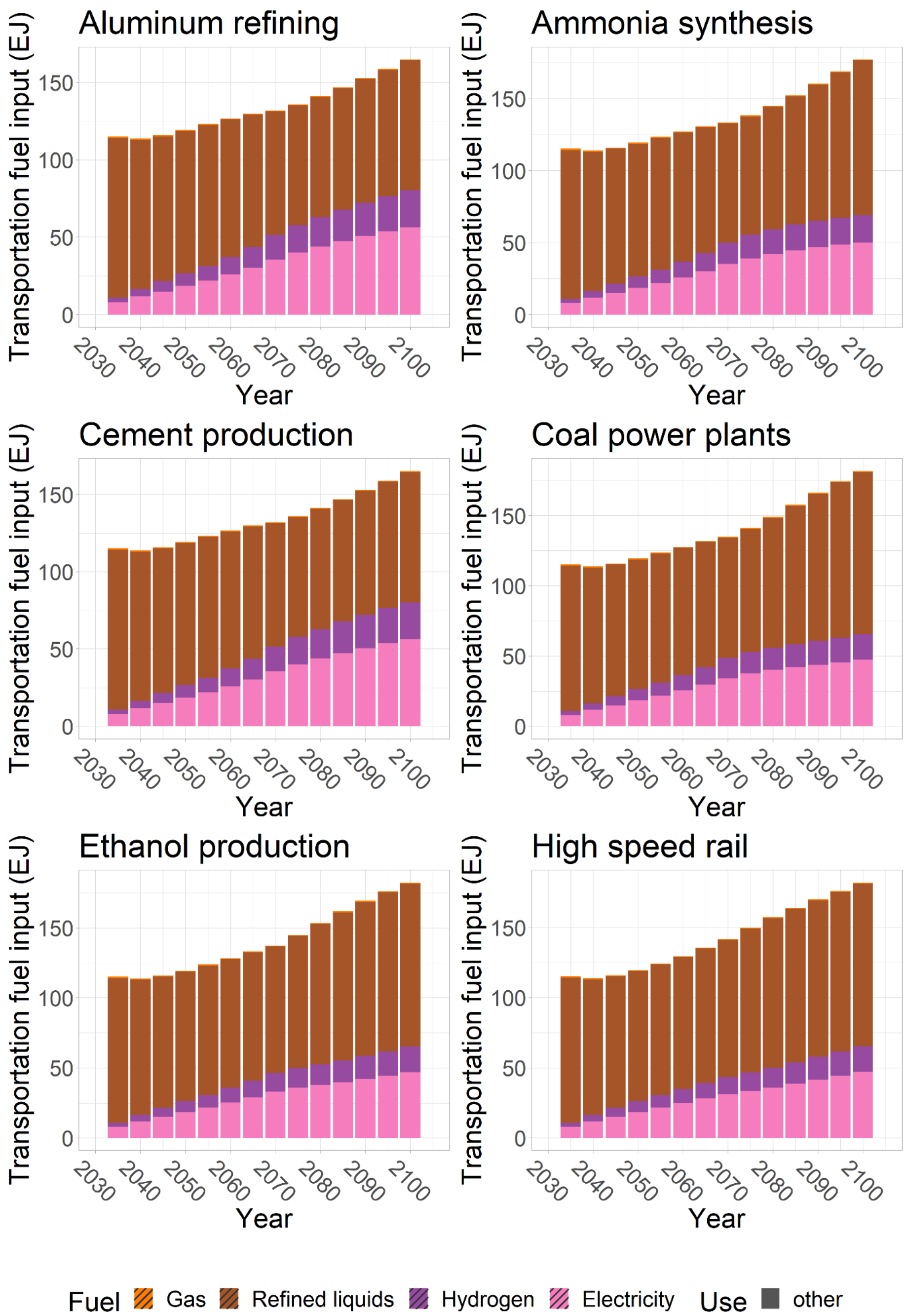

Figure S16: *Final transportation energy demand by fuel source for the DACCS adoption pathways based on six analogs: aluminum refining, ammonia synthesis, cement production, coal power plants, ethanol production, and high speed rail.*

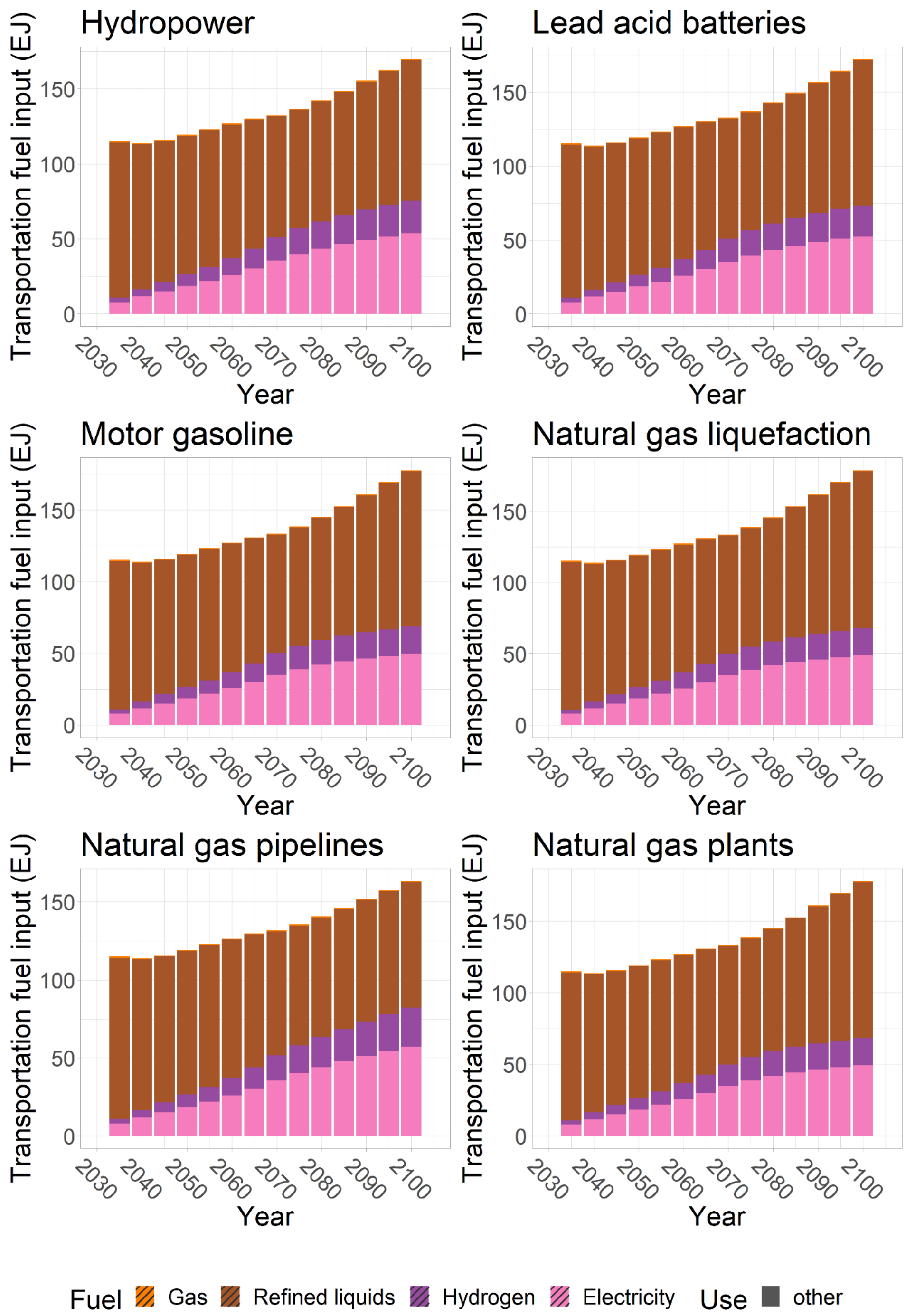

Figure S17: *Final transportation energy demand by fuel source for the DACCS adoption pathways based on six analogs: hydropower, lead acid batteries, motor gasoline, natural gas liquefaction, natural gas pipelines, and natural gas plants.*

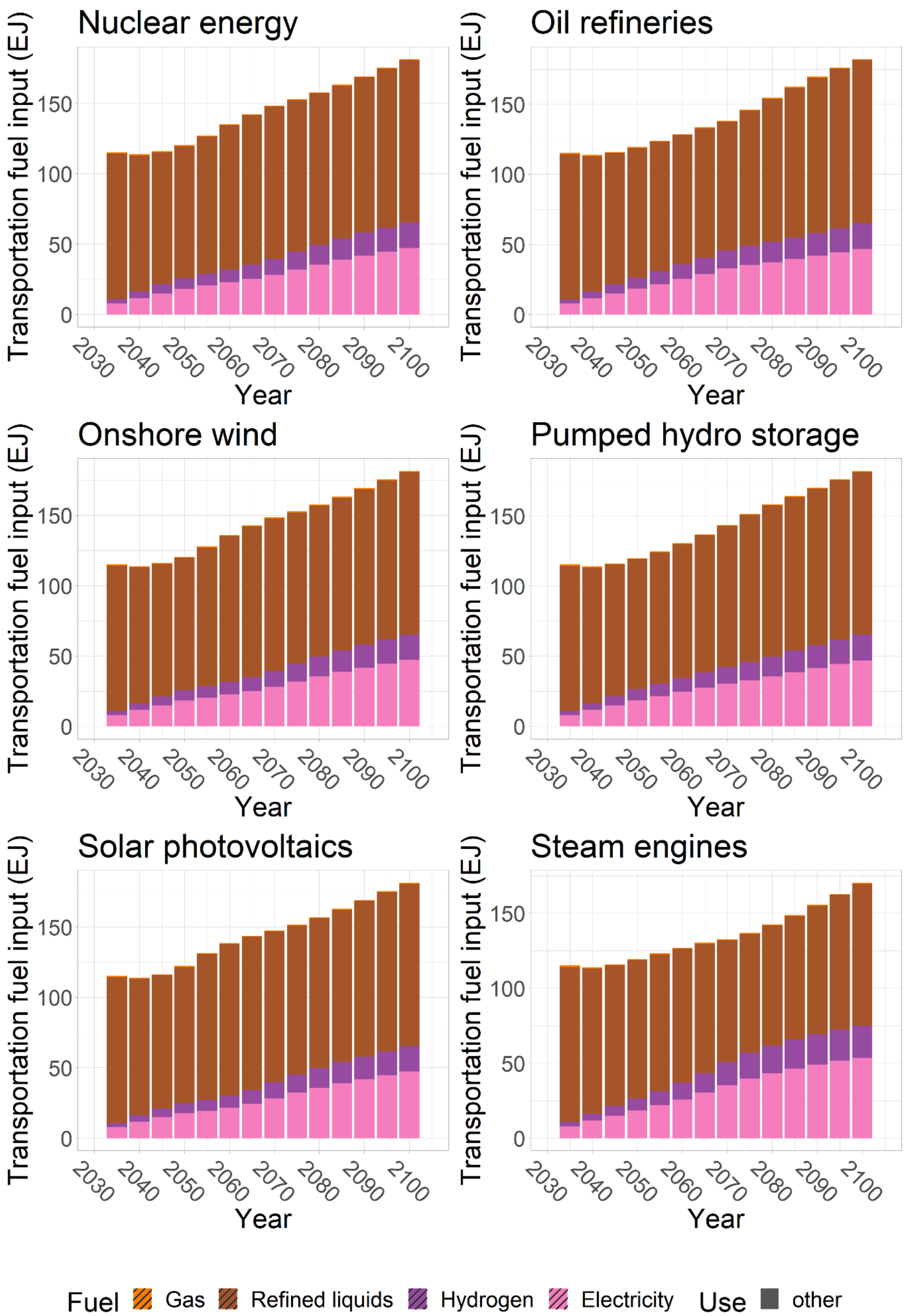

Figure S18: *Final transportation energy demand by fuel source for the DACCS adoption pathways based on six analogs: nuclear energy, oil refineries, onshore wind, pumped hydro storage, solar photovoltaics, steam engines.*

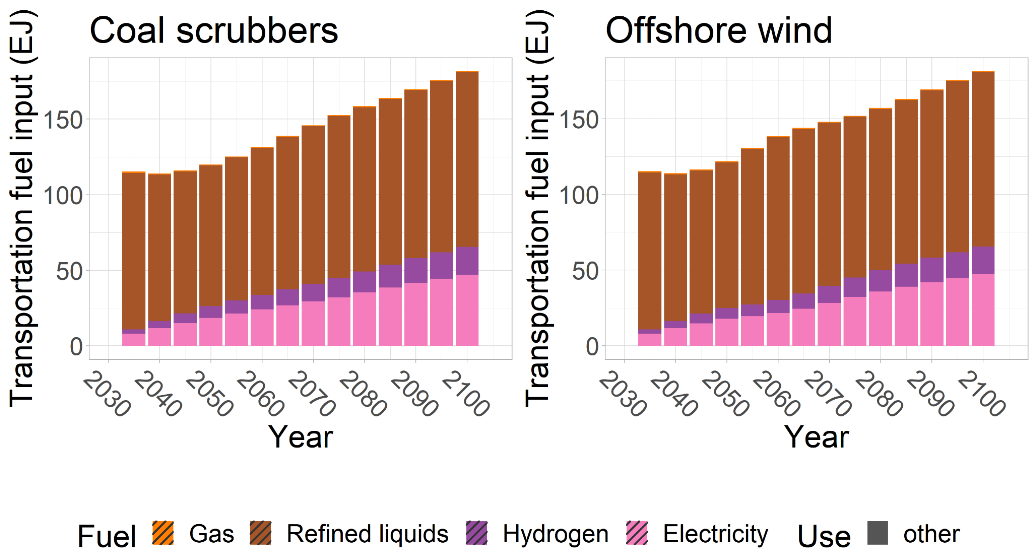

Figure S19: *Final transportation energy demand by fuel source for the two DACCS adoption pathways based on two analogs: coal scrubber and offshore wind.*

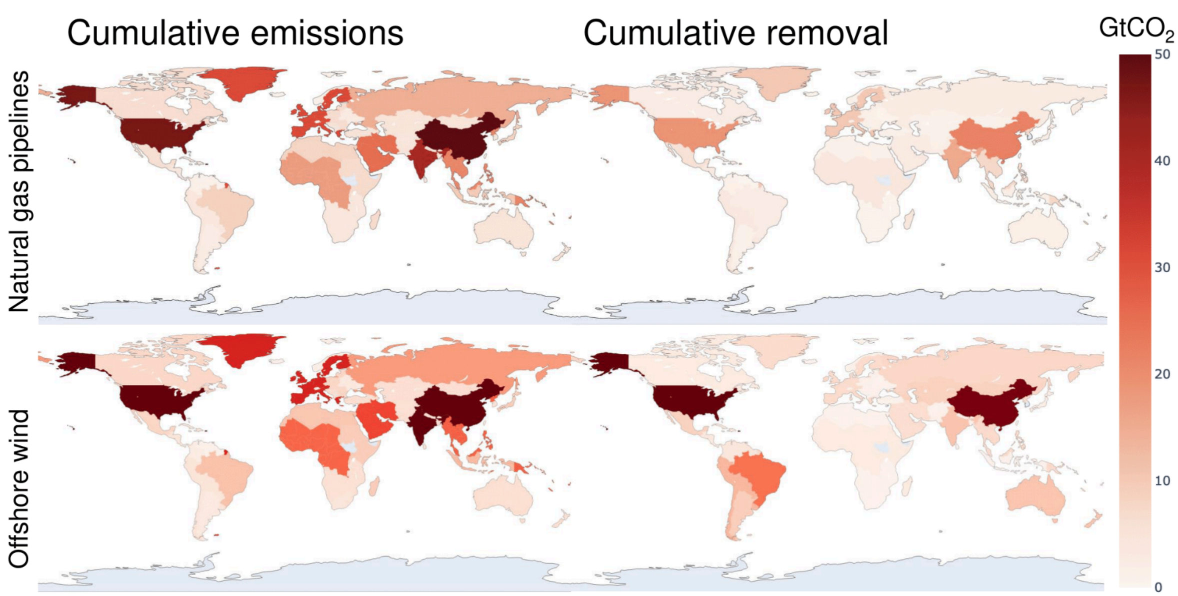

Figure S20: *Regional distribution of cumulative CO_2 emissions (left) and sequestration (right) when DACCS grows at the same rate as natural gas pipelines (top) and offshore wind (bottom).*

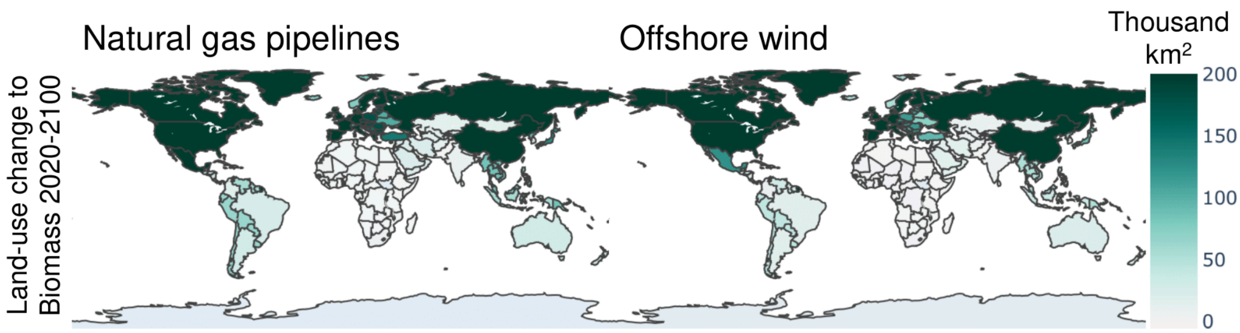

__Figure S21:__ Regional distribution of cumulative land use change to biomass for energy when DACCS grows at the same rates as natural gas pipelines (left) and offshore wind (right)

References

1. L. D. Anadon, *et al.*, Making technological innovation work for sustainable development. *Proc. Natl. Acad. Sci.* **113**, 9682–9690 (2016).
2. C. Wilson, *et al.*, Granular technologies to accelerate decarbonization. *Science* **368**, 36–39 (2020).
3. A. Malhotra, T. S. Schmidt, Accelerating Low-Carbon Innovation. *Joule* **4**, 2259–2267 (2020).
4. B. Nagy, J. D. Farmer, Q. M. Bui, J. E. Trancik, Statistical Basis for Predicting Technological Progress. *PLOS ONE* **8**, e52669 (2013).
5. L. M. A. Bettencourt, J. E. Trancik, J. Kaur, Determinants of the Pace of Global Innovation in Energy Technologies. *PLOS ONE* **8**, e67864 (2013).
6. J. Meng, R. Way, E. Verdolini, L. D. Anadon, Comparing expert elicitation and model-based probabilistic technology cost forecasts for the energy transition. *Proc. Natl. Acad. Sci.* **118** (2021).
7. G. Kavlak, J. McNerney, J. E. Trancik, Evaluating the causes of cost reduction in photovoltaic modules. *Energy Policy* **123**, 700–710 (2018).
8. G. F. Nemet, Beyond the learning curve: factors influencing cost reductions in photovoltaics. *Energy Policy* **34**, 3218–3232 (2006).
9. J. McNerney, J. Doyne Farmer, J. E. Trancik, Historical costs of coal-fired electricity and implications for the future. *Energy Policy* **39**, 3042–3054 (2011).
10. M. G. Morgan, Use (and abuse) of expert elicitation in support of decision making for public policy. *Proc. Natl. Acad. Sci.* **111**, 7176–7184 (2014).
11. L. Diaz Anadon, E. Verdolini, E. Baker, V. Bosetti, L. Reis, Future prospects for energy technologies: insights from expert elicitations (2018) https:/doi.org/10.17863/CAM.26160 (January 19, 2022).
12. E. Baker, V. Bosetti, L. D. Anadon, M. Henrion, L. Aleluia Reis, Future costs of key low-carbon energy technologies: Harmonization and aggregation of energy technology expert elicitation data. *Energy Policy* **80**, 219–232 (2015).
13. S. Shayegh, V. Bosetti, M. Tavoni, Future Prospects of Direct Air Capture Technologies: Insights From an Expert Elicitation Survey. *Front. Clim.* **3** (2021).
14. J. D. Farmer, F. Lafond, How predictable is technological progress? *Res. Policy* **45**, 647–665 (2016).
15. G. Nemet, J. Greene, F. Müller-Hansen, J. C. Minx, Dataset on the adoption of historical technologies informs the scale-up of emerging carbon dioxide removal measures. *Commun. Earth Environ.* **4**, 1–10 (2023).
16. A. Grubler, *et al.*, A low energy demand scenario for meeting the 1.5 °C target and sustainable development goals without negative emission technologies. *Nat. Energy* **3**, 515–527 (2018).
17. A. Cherp, V. Vinichenko, J. Tosun, J. A. Gordon, J. Jewell, National growth dynamics of wind and solar power compared to the growth required for global climate targets. *Nat. Energy* **6**, 742–754 (2021).
18. F. Creutzig, *et al.*, The underestimated potential of solar energy to mitigate climate change. *Nat. Energy* **2**, 1–9 (2017).
19. N. Bento, C. Wilson, Measuring the duration of formative phases for energy technologies. *Environ. Innov. Soc. Transit.* **21**, 95–112 (2016).
20. N. Bento, C. Wilson, L. D. Anadon, Time to get ready: Conceptualizing the temporal and spatial dynamics of formative phases for energy technologies. *Energy Policy* **119**, 282–293 (2018).
21. Everett M. Rogers, *Diffusion of Innovations* (Free Press of Glencoe, 1962).
22. D. Kucharavy, R. De Guio, Logistic substitution model and technological forecasting.

Procedia Eng. **9**, 402–416 (2011).
23. E. M. Rogers, Characterizing the adopters of agricultural practices. *Rural Sociol.* **23**, 346–354 (1958).
24. S. Jacobsson, V. Lauber, The politics and policy of energy system transformation—explaining the German diffusion of renewable energy technology. *Energy Policy* **34**, 256–276 (2006).
25. A. Cherp, V. Vinichenko, J. Tosun, J. A. Gordon, J. Jewell, National growth dynamics of wind and solar power compared to the growth required for global climate targets. *Nat. Energy* **6**, 742–754 (2021).
26. IEA, "Direct Air Capture 2022" (2022). https://www.iea.org/reports/direct-air-capture-2022.
27. Global Thermostat, Global Thermostat unveils one of the world's largest units for removing carbon dioxide directly from air (2023) (September 13, 2023). https://www.prnewswire.com/news-releases/global-thermostat-unveils-one-of-the-worlds-largest-units-for-removing-carbon-dioxide-directly-from-air-301789992.html
28. N. Bento, C. Wilson, Measuring the duration of formative phases for energy technologies. *Environ. Innov. Soc. Transit.* **21**, 95–112 (2016).
29. Z. Griliches, Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica* **25**, 501–522 (1957).
30. C. Marchetti, N. Nakicenovic, "Dynamics of energy systems and the logistic substitution model" (IIASA, 1980) (September 7, 2023).
31. R. J. Lowe, P. Drummond, Solar, wind and logistic substitution in global energy supply to 2050 – Barriers and implications. *Renew. Sustain. Energy Rev.* **153**, 111720 (2022).
32. K. U. Rao, V. V. N. Kishore, A review of technology diffusion models with special reference to renewable energy technologies. *Renew. Sustain. Energy Rev.* **14**, 1070–1078 (2010).
33. A. Grubler, N. Nakicenovic, D. G. Victor, Dynamics of Energy Technologies and Global Change. 40 (1999).
34. T. Napp, *et al.*, Exploring the Feasibility of Low-Carbon Scenarios Using Historical Energy Transitions Analysis. *Energies* **10**, 116 (2017).
35. S. van Ewijk, W. McDowall, Diffusion of flue gas desulfurization reveals barriers and opportunities for carbon capture and storage. *Nat. Commun.* **11**, 4298 (2020).
36. A. Grubler, C. Wilson, G. Nemet, Apples, oranges, and consistent comparisons of the temporal dynamics of energy transitions. *Energy Res. Soc. Sci.* **22**, 18–25 (2016).
37. A. Odenweller, F. Ueckerdt, G. F. Nemet, M. Jensterle, G. Luderer, Probabilistic feasibility space of scaling up green hydrogen supply. *Nat. Energy* **7**, 854–865 (2022).
38. C. Wilson, A. Grubler, N. Bauer, V. Krey, K. Riahi, Future capacity growth of energy technologies: are scenarios consistent with historical evidence? *Clim. Change* **118**, 381–395 (2013).
39. R. Way, M. C. Ives, P. Mealy, J. D. Farmer, Empirically grounded technology forecasts and the energy transition. *Joule* (2022) https:/doi.org/10.1016/j.joule.2022.08.009 (September 16, 2022).
40. J. C. Fischer, R. H. Pry, A Simple Substitution Model of Technological Change. *Technol. Forecast. Soc. Change* **3**, 75–88 (1971).
41. C. Wilson, Up-scaling, formative phases, and learning in the historical diffusion of energy technologies. *Energy Policy* **50**, 81–94 (2012).
42. A. Debecker, T. Modis, Determination of the uncertainties in S-curve logistic fits. *Technol. Forecast. Soc. Change* **46**, 153–173 (1994).
43. G. C. Iyer, *et al.*, Improved representation of investment decisions in assessments of CO_2 mitigation. *Nat. Clim. Change* **5**, 436–440 (2015).
44. L. Clarke, J. Weyant, J. Edmonds, On the sources of technological change: What do the models assume? *Energy Econ.* **30**, 409–424 (2008).

45. E. S. Rubin, J. E. Davison, H. J. Herzog, The cost of CO_2 capture and storage. *Int. J. Greenh. Gas Control* **40**, 378–400 (2015).
46. V. Krey, *et al.*, Looking under the hood: A comparison of techno-economic assumptions across national and global integrated assessment models. *Energy* **172**, 1254–1267 (2019).
47. C. Roberts, G. Nemet, Systematic Historical Analogue Research for Decision-making (SHARD): Introducing a new methodology for using historical case studies to inform low-carbon transitions. *Energy Res. Soc. Sci.* **93**, 102768 (2022).
48. C. Roberts, F. W. Geels, Conditions for politically accelerated transitions: Historical institutionalism, the multi-level perspective, and two historical case studies in transport and agriculture. *Technol. Forecast. Soc. Change* **140**, 221–240 (2019).
49. F. W. Geels, The multi-level perspective on sustainability transitions: Responses to seven criticisms. *Environ. Innov. Soc. Transit.* **1**, 24–40 (2011).
50. E. S. Rubin, I. M. L. Azevedo, P. Jaramillo, S. Yeh, A review of learning rates for electricity supply technologies. *Energy Policy* **86**, 198–218 (2015).
51. J. Jewell, A. Cherp, The feasibility of climate action: Bridging the inside and the outside view through feasibility spaces. *WIREs Clim. Change* **14**, e838 (2023).
52. S. Low, S. Schäfer, Is bio-energy carbon capture and storage (BECCS) feasible? The contested authority of integrated assessment modeling. *Energy Res. Soc. Sci.* **60**, 101326 (2020).
53. N. E. Hultman, *et al.*, Fusing subnational with national climate action is central to decarbonization: the case of the United States. *Nat. Commun.* **11**, 5255 (2020).
54. W. Peng, *et al.*, Climate policy models need to get real about people — here's how. *Nature* **594**, 174–176 (2021).
55. J. D. Jenkins, Political economy constraints on carbon pricing policies: What are the implications for economic efficiency, environmental efficacy, and climate policy design? *Energy Policy* **69**, 467–477 (2014).
56. W. Peng, *et al.*, To achieve deep cuts in US emissions, state-driven policy is only slightly more expensive than nationally uniform policy. *Nat. Clim. Change* **11**, 911–912 (2021).
57. E. Trutnevyte, *et al.*, Societal Transformations in Models for Energy and Climate Policy: The Ambitious Next Step. *One Earth* **1**, 423–433 (2019).
58. L. Steg, *et al.*, A method to identify barriers to and enablers of implementing climate change mitigation options. *One Earth* **5**, 1216–1227 (2022).
59. T. S. Schmidt, Low-carbon investment risks and de-risking. *Nat. Clim. Change* **4**, 237–239 (2014).
60. IPCC, Ed., "Mitigation Pathways Compatible with 1.5°C in the Context of Sustainable Development" in *Global Warming of 1.5°C: IPCC Special Report on Impacts of Global Warming of 1.5°C above Pre-Industrial Levels in Context of Strengthening Response to Climate Change, Sustainable Development, and Efforts to Eradicate Poverty*, (Cambridge University Press, 2022), pp. 93–174.
61. J. Jewell, A. Cherp, On the political feasibility of climate change mitigation pathways: Is it too late to keep warming below 1.5°C? *WIREs Clim. Change* **11**, e621 (2020).
62. Intergovernmental Panel on Climate Change (IPCC), "Summary for Policymakers" in *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, (Cambridge University Press, 2023), pp. 3–34.
63. R. Pielke, T. Wigley, C. Green, Dangerous assumptions. *Nature* **452**, 531–532 (2008).
64. G. Kavlak, J. McNerney, R. L. Jaffe, J. E. Trancik, Metal production requirements for rapid photovoltaics deployment. *Energy Environ. Sci.* **8**, 1651–1659 (2015).
65. J. Fuhrman, *et al.*, The role of direct air capture and negative emissions technologies in the shared socioeconomic pathways towards +1.5 °C and +2 °C futures. *Environ. Res.*

Lett. **16**, 114012 (2021).
66. E. Byers, *et al.*, AR6 Scenarios Database (2022) https:/doi.org/10.5281/zenodo.7197970 (October 10, 2023).
67. H. J. Buck, W. Carton, J. F. Lund, N. Markusson, Why residual emissions matter right now. *Nat. Clim. Change* **13**, 351–358 (2023).
68. N. Grant, A. Gambhir, S. Mittal, C. Greig, A. C. Köberle, Enhancing the realism of decarbonisation scenarios with practicable regional constraints on CO_2 storage capacity. *Int. J. Greenh. Gas Control* **120**, 103766 (2022).
69. J. Lane, C. Greig, A. Garnett, Uncertain storage prospects create a conundrum for carbon capture and storage ambitions. *Nat. Clim. Change* **11**, 925–936 (2021).
70. J. Fuhrman, *et al.*, Diverse carbon dioxide removal approaches could reduce impacts on the energy–water–land system. *Nat. Clim. Change* **13**, 341–350 (2023).
71. Y. Ou, *et al.*, Deep mitigation of CO_2 and non-CO_2 greenhouse gases toward 1.5 °C and 2 °C futures. *Nat. Commun.* **12**, 1–9 (2021).
72. J. Greene, G. Nemet, The Historical Adoption of TeCHnology (HATCH) Database (2023) https:/doi.org/https://cdr.apps.ece.iiasa.ac.at/story/hatch/. [Accessed 12 January, 2024].
73. Global Energy Monitor, Global Gas Infrastructure Tracker (2022) (September 21, 2023).
74. International Gas Union, “World LNG Report” (IGU, 2022).
75. C. Roberts, G. F. Nemet, Lessons for Direct Air Capture from the History of Nitrogen Synthesis: High Rates of Deployment are Possible, with Strong Support. *Technol. Forecast. Soc. Change* (In press).
76. R. Hanna, A. Abdulla, Y. Xu, D. G. Victor, Emergency deployment of direct air capture as a response to the climate crisis. *Nat. Commun.* **12**, 1–13 (2021).
77. D. W. Keith, G. Holmes, D. S. Angelo, K. Heidel, A Process for Capturing CO_2 from the Atmosphere. *Joule* **2**, 1573–1594 (2018).
78. K. Surana, C. Doblinger, L. D. Anadon, N. Hultman, Effects of technology complexity on the emergence and evolution of wind industry manufacturing locations along global value chains. *Nat. Energy* **5**, 811–821 (2020).
79. National Energy Technology Lab, 8.8. Sulfur Oxides (SOx) Emissions From Coal. *Department of Energy* (October 10, 2023). https://www.netl.doe.gov/research/coal/energy-systems/gasification/gasifipedia/sox-emissions
80. Direct Air Capture Advisory Council, “The Commercial Case for Direct Air Capture” (Bipartisan Policy Center, 2021).
81. P. Virtanen, *et al.*, SciPy 1.0: fundamental algorithms for scientific computing in Python. *Nat. Methods* **17**, 261–272 (2020).
82. IEA, ETP Clean Energy Technology Guide (2023) (September 12, 2023). https://www.iea.org/data-and-statistics/data-tools/etp-clean-energy-technology-guide
83. IEA, CCUS Projects Database (2023). https://www.iea.org/data-and-statistics/data-product/ccus-projects-database
84. S. M. Smith, *et al.*, “The State of Carbon Dioxide Removal - 1st Edition” (The State of Carbon Dioxide Removal, 2023) https:/doi.org/10.17605/OSF.IO/W3B4Z.
85. R. Höglund, K. Niparko, cdr.fyi (September 12, 2023).
86. i3, Cleantech Group i3 Database (January 19, 2022). https://i3connect.com
87. Stripe, Climate Carbon Removal Purchases - Source Materials (2023) (April 25, 2023). https://github.com/stripe/carbon-removal-source-materials
88. Office of Fossil Energy and Carbon Management, Project Selections for FOA 2735: Regional Direct Air Capture Hubs – Topic Area 1 (Feasibility) and Topic Area 2 (Design). *Energy.gov* (October 10, 2023). https://www.energy.gov/fecm/project-selections-foa-2735-regional-direct-air-capture-hubs-topic-area-1-feasibility-and

89. Bipartisan Policy Center, Direct Air Capture: Investment Snapshot (2021). https://bipartisanpolicy.org/download/?file=/wp-content/uploads/2021/02/Bipartisan_Energy-DAC-Fact-Sheet-Part-4_R01_2.5.2021edits.pdf
90. CarbonCollect, Mechanical Tree (October 5, 2023). https://carboncollect.com/mechanical-tree/
91. L. Collins, HIF Global gets green light to build world's largest e-fuels facility in Texas — with 1.8GW of green hydrogen production | Hydrogen news and intelligence. *HydrogenInsight* (2023) (October 5, 2023).
92. HIF Global, Haru Oni. *HIF Glob.* (September 12, 2023). https://hifglobal.com/location/haru-oni/
93. P. Trendafilova, New Direct Air Capture Startup Removr Secures $3.51M Government Grant. *Carbon Her.* (2023) (October 23, 2023).
94. Global Thermostat, News and Updates (October 23, 2023). https://www.globalthermostat.com/news-and-updates
95. Climeworks, Orca: the first large-scale plant (April 25, 2023). https://climeworks.com/plant-orca
96. Prometheus Fuels, Demo 3's Got a Brand New DAC System (October 23, 2023). https://prometheusfuels.com
97. Nordic DAC Group, Newsroom. *Nord. DAC Group* (October 23, 2023). https://www.nordicdacgroup.com/newsroom/
98. H. Griffin, Oxy Low Carbon Ventures, Rusheen Capital Management create development company 1PointFive to deploy Carbon Engineering's Direct Air Capture technology. *Carbon Eng.* (2020) (October 23, 2023).
99. Carbon Capture, Newsroom (October 23, 2023). https://www.carboncapture.com/newsroom
100. Occidental, Construction of World's Largest Direct Air Capture Plant in the Texas Permian Basin. *1PointFive* (2022) (October 5, 2023).
101. G. F. Nemet, *How Solar Energy Became Cheap: A Model for Low-Carbon Innovation* (Routledge, 2019).
102. B. Bond-Lamberty, *et al.*, GCAM 6.0 (2022) https:/doi.org/10.5281/zenodo.6619287 (April 26, 2023).
103. A. Ho, J. Taylor, "Using Advance Market Commitments for Public Purpose Technology Development" (Belfer Center for Science and International Affairs, Harvard Kennedy School, 2021).
104. Frontier Climate, Launch (2021) (October 19, 2023). https://frontierclimate.com/writing/launch
105. A. Goldstein, C. Doblinger, E. Baker, L. D. Anadón, Patenting and business outcomes for cleantech startups funded by the Advanced Research Projects Agency-Energy. *Nat. Energy* **5**, 803–810 (2020).
106. M. Mazzucato, G. Semieniuk, Public financing of innovation: new questions. *Oxf. Rev. Econ. Policy* **33**, 24–48 (2017).
107. K. S. Gallagher, A. Grübler, L. Kuhl, G. Nemet, C. Wilson, The energy technology innovation system. *Annu. Rev. Environ. Resour.* **37**, 137–162 (2012).
108. K. Surana, *et al.*, The role of corporate investment in start-ups for climate-tech innovation. *Joule*, S2542435123000879 (2023).
109. C. Doblinger, K. Surana, L. D. Anadon, Governments as partners: The role of alliances in U.S. cleantech startup innovation. *Res. Policy* **48**, 1458–1475 (2019).
110. Crunchbase, Discover innovative companies and the people behind them. *Crunchbase* (May 3, 2023).
111. US DOE, Biden-Harris Administration Announces Up To $1.2 Billion For Nation's First Direct Air Capture Demonstrations in Texas and Louisiana. *Energy.gov* (October 19,

2023).