Direct Air Capture as a Carbon Removal Solution: Analyzing Scale-Up, Cost Reduction, and Pathways for Acceleration

by

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B.S. Petroleum Engineering, West Virginia University, 2013

Submitted to the System Design and Management Program
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ABSTRACT

In addition to drastic reductions in global carbon dioxide emissions, the Intergovernmental Panel on Climate Change has stated with high confidence that carbon dioxide removal will be needed to meet the Paris Agreement temperature goals. Direct air capture is a novel carbon removal technique that is gaining attention for its potential contribution to the portfolio of carbon removal solutions. As its primary barrier to deployment is high costs, there is a focus on understanding how this technology could reach lower costs by mid-century.

This thesis uses technological change theory to investigate potential scale-up and cost-reduction forecasts for existing direct air capture methods. The literature review provides context for carbon dioxide removal, direct air capture, and technological change theory. Analogous technologies are reviewed for cost-reduction drivers and compared to the common direct air capture methods. This comparison is used for learning and improvement rate analysis to estimate cost reduction forecasts for mature direct air capture methods, then used to identify levers that direct air capture stakeholders can deploy to accelerate scale-up and cost reductions.

The results suggest solid sorbent direct air capture (S-DAC) could achieve costs of \$100-\$400/tonCO_2 by 2050, while liquid solvent direct air capture (L-DAC) may reach \$100-\$220/tonCO_2 in the same period. For the base assumptions investigated, S-DAC reaches the 45Q U.S. tax credit threshold in 2041 using a single-factor improvement rate analysis and in 2040 using component-based. L-DAC reaches the threshold in 2034 for single-factor and in 2037 for component-based improvement rates. Neither method reaches the threshold using a single-factor or component-based learning rate analysis under base assumptions.

The analog analysis emphasizes the importance of a variety of direct air capture stakeholders in accelerating the technology's scale-up and cost reductions. Policymakers can develop standards for measurement, reporting, and verification of carbon dioxide removal. The private sector can set clear requirements for carbon removal purchases focusing on proven, durable, measurable methods with clear paths for cost reductions. Direct air capture providers can focus on early design choices that enable cost reductions and work to build economies of scale in manufacturing. The findings indicate that the technology may reach cost-competitive thresholds by mid-century and that stakeholders across the direct air capture ecosystem have opportunities to accelerate this transition.

Thesis supervisor: Dr. Bruce G. Cameron
Title: Director, System Architecture Group

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List of Acronyms

AMCs	Advance Market Commitments
BECCS	Bioenergy with Carbon Capture and Storage
CAPEX	Capital Expense
CCGT	Combined Cycle Gas Turbine
CO_2	Carbon Dioxide
CDR	Carbon Dioxide Removal
DAC	Direct Air Capture
DACCS	Direct Air Carbon Capture with Storage
ERW	Enhanced Rock Weathering
ESA-DAC	Electro-Swing Adsorption Direct Air Capture
FOAK	First of a Kind
GHG	Greenhouse Gas
GTCC	Gas Turbine Combined Cycle
IAM	Integrated Assessment Model
IEA	International Energy Agency
IIJA	Infrastructure Investment and Jobs Act
IPCC	Intergovernmental Panel on Climate Change
IRA	Inflation Reduction Act
L-DAC	Liquid Absorbent Direct Air Capture
LR	Learning Rate
m-DAC	Membrane-Based Direct Air Capture
MRV	Monitoring, Reporting, and Verification
MSA	Moisture Swing Adsorption
NET	Negative Emission Technology
NGCC	Natural Gas Combined Cycle
OPEX	Operating Expense
PSC	Point Source Capture
PV	Photovoltaic
S-DAC	Solid Adsorbent Direct Air Capture
TSA	Temperature Swing Adsorption
UNFCCC	United Nations Framework Convention on Climate Change
VSA	Vacuum Swing Adsorption

Chapter 1

Introduction

1.1 Motivation

Over the last several years, there has been an increasing consensus within the scientific community that in order to meet the goal of holding below a change of 1.5-2°C compared to pre-industrial levels, directly removing carbon dioxide (CO_2) from the atmosphere and permanently storing it will be necessary [46], [49], [53], [96]. While ongoing efforts to abruptly lower our current emission levels will remain the critical focus for achieving these objectives, accelerating the understanding and commercialization of carbon removal options must be accomplished in parallel. The UN Intergovernmental Panel on Climate Change (IPCC)'s Sixth Assessment Report section released in April 2022 states, "Pathways that limit warming to 2°C (>67%) or lower involve some amount of CDR to compensate for residual greenhouse gas emissions remaining after substantial direct emissions reductions in all sectors and regions (high confidence)" [53].

The techniques of directly removing carbon dioxide from the atmosphere are generally referred to as Carbon Dioxide Removal (CDR) techniques. These range from more conventional techniques that are land-based and immediately available, such as afforestation and reforestation, to novel techniques that utilize a variety of approaches to store carbon[1] geologically, in the ocean, or in products. The majority of these novel techniques are still in development or in the very early stages of implementation [96]. Examples include direct air capture (DAC) with carbon capture and storage (DACCS), enhanced rock weathering (ERW), and bioenergy with carbon capture and storage (BECCS).

According to the 2023 report "The Current State of Carbon Dioxide Removal", the CDR activities in operation today remove approximately 2 $GtCO_2$ per year, almost all from conventional techniques focused on land management [96]. In contrast, only approximately 0.002 $GtCO_2$ per year of removal comes from novel techniques at present [96]. Considering the IPCC's estimate of needing 2.8 (0.5-11 range) $GtCO_2$ per year of non-conventional removal in 1.5°C scenarios by 2050, there is considerable scaling that needs to be accomplished over the next 25 years [53].

[1]For ease of reading, "carbon" will be used interchangeably with "CO_2" and "carbon dioxide" throughout this thesis.

1.2 Background

While a large portfolio of CDR techniques will likely be needed, a significant portion of future removal is expected to come from novel techniques. Many of these techniques have lower land-use requirements than conventional techniques, as well as more options for higher storage durability [96]. DAC is a novel technique in particular that has gained significant attention in both industry and the public sector recently, largely due to its clarity in measurement and verification of the amount of carbon removed and stored compared to other techniques [44].

Unfortunately, DAC does come with complex challenges. Unlike the more traditional point source capture used in industrial plants to capture CO_2 in post-combustion processes where concentrations may range from 3%-30%, DAC captures carbon from ambient air where concentrations are closer to 0.041% [36]. This means that it has to process vast amounts of ambient air to capture worthwhile amounts of carbon to store. Another key challenge is the amount of energy that is needed to facilitate this process, made even more difficult if it must be clean energy to avoid additional carbon emissions. These two challenges lead to the largest overarching challenge for this technology: cost.

Despite these challenges, Climeworks became the first company to sell third-party certified CDR services to several corporate clients, including Microsoft, Shopify, and Stripe, through their DAC technology in January 2023 through a partnership with Carbfix to geologically sequester the captured carbon [7]. The U.S. Government has also shown keen interest in supporting this technology development through recent legislation. The 2021 Infrastructure Investment and Jobs Act committed over $3.5 billion in funding for the development of four regional DAC hubs across the country, with varying levels of support to be rewarded depending on the phase of development (feasibility, design, or build) [68]. The 2022 Inflation Reduction Act also substantially increased the 45Q tax credit support for DAC, going from $50/tonne of CO_2 with DAC to $180/tonne with geologic storage from DAC and to $130/tonne with utilization from DAC [44].

Similar to how CDR techniques can be broken down into multiple types of removal, DAC can be decomposed into many different methods of capture. The two most common methods are using solid adsorbents (S-DAC) and using liquid aqueous basic solutions (L-DAC), both of which are energy intensive [46]. However, many additional emerging methods try to address the issue of high-energy use through novel methods such as electro-swing processes and moisture swing adsorption [76]. These are much earlier in development but could provide future scalable optionality.

For technology this early in development, it is important to consider how and when it will transition from prototype and demonstration to commerciality. In the report "Accelerating the Low Carbon Transition", Victor et al. describe three key phases in any system transition: emergence, diffusion, and reconfiguration. The emergence phase is characterized by the formation of many niches for a new technology, where buyers in the niches are willing to pay much more for the technology than the average buyer, unique use cases are identified, and experimentation and learning are prevalent. This is where DAC currently lies as it starts to find niche markets like early government investment and private sector funding. Movement to the diffusion stage may occur if costs can be lowered through additional innovation, higher technical performance emerges, and functional requirements are better defined. [104]

1.3 Objectives

As with any creation of a new market, scaling up CDR will take time and is bound to encounter various complex challenges along the way. In the case of direct air capture, successful deployment is tightly linked to its ability to come down the cost curve swiftly. This thesis aims to shed light on this process by addressing the following essential questions, seeking to unravel the potential trajectory of these cost reductions:

1. The IPCC estimates needing 2.8 (0.5-11 range) $GtCO_2$/yr of non-conventional carbon removal by 2050, but current removal rates are well below this. If DAC adoption and cost reduction behave similarly to solar PV or other analogous technologies, what contribution can it realistically expect to make to the CO_2 removal portfolio?
   (a) How might scale-up rate and cost reduction vary by DAC method?
   (b) What does the literature identify as the key drivers for analogous technology learning and improvement, and how do those compare to the various DAC methods?
   (c) What role are the public and private sectors currently playing in advancing the DAC market, and how does this compare to analogs?
2. Based on the answers to Question 1, what actions could be taken in the near term regarding DAC by governments, DAC providers, and DAC purchasers to help accelerate the reduction of DAC costs?

1.4 Outline

To facilitate the investigation of the research questions in Section 1.3, this thesis is structured as follows:

- **Literature Review**: Chapter 2 provides an overview of the current direct air capture landscape as relevant to this thesis. It begins with context around CDR and how DAC fits into the emerging CDR portfolio. It then zooms in directly to DAC, describing how it works, key barriers to implementation, and its current and forecasted ecosystem. Finally, a review of the literature regarding technological learning and improvement provides a framework for exploring the potential cost-reduction pathways of DAC.
- **Method and Framework**: Chapter 3 begins by framing the methods that are used for the analysis. It then collects and documents key assumptions and inputs utilized by the analysis.
- **Results**: Chapter 4 reports the results of the analysis. It begins with the analog assessment results for each DAC technique, then provides the results of the cost reduction forecasts. It concludes with sensitivities to help give context to the range of potential outcomes.

- **Discussion**: Chapter 5 describes the insights gained from the analysis results through the lens of the research questions. Based on those insights, actions that stakeholders within the DAC industry may take to accelerate cost reductions are proposed.

- **Conclusions**: Chapter 6 provides conclusions and recommendations for governments, DAC providers, and DAC purchasers to help accelerate the reduction of DAC costs given the results of the analysis. It also lays out recommendations for future studies in this field.

Chapter 2

Literature Review

Context around three key concepts is important background information to understand for this thesis. These include types of and need for carbon dioxide removal; understanding of direct air capture and its ecosystem; and the theory of technological change. This chapter provides the context for each concept and helps bring the reader up to speed on the research landscape relevant to the analysis.

2.1 Carbon Dioxide Removal

Historical anthropogenic greenhouse gas emissions, particularly over the past century, have caused a gradual increase in the earth's average temperature [50]. The annual carbon dioxide equivalent emissions at a global level have almost reached 40 $GtCO_2$/yr as of 2022 [43]. "Natural" land and ocean sinks can absorb about one-half of this emission rate, but after years of emissions exceeding sink capacity, an overall increase in atmospheric CO_2 concentration of approximately 125ppm over the last 150 years has been observed [80]. A focused international effort is underway to lower these emissions to curb this warming and the effects it is having on the planet.

In 2015, 195 of 198 parties within the United Nations Framework Convention on Climate Change (UNFCCC) signed the Paris Agreement [102]. This agreement was a strong recognition of climate change and the first major binding agreement across this many countries to take action to address it [103]. The agreement includes the following objective, which will hereto be referred to as the Paris Temperature Goal within this thesis:

> *"Holding the increase in the global average temperature to well below 2°C above preindustrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels."*

This temperature goal remains the point of reference for most modeling efforts from the major climate change bodies. While it does not specify a timeframe in which to accomplish the goal, using the phrase "holding below" indicates the intent is to avoid overshooting this temperature at any point in the future.

It is recognized that in order to meet the Paris Temperature Goal, carbon dioxide emissions will need to be significantly reduced worldwide. The techniques associated with these emission reductions are commonly referred to as climate mitigation options, which can include options like replacing fossil fuel use with renewable energy, increasing the energy efficiency of existing systems, or capturing carbon emitted when burning fossil fuels before it is released into the atmosphere [53]. These strong reductions in emissions are critical to combating climate change and should occur as rapidly as possible using a portfolio of mitigation techniques.

One additional mitigation technique that is emerging as a key contributor to climate change efforts is Carbon Dioxide Removal (CDR). Climate mitigation scenarios that included CDR were first included in the Intergovernmental Panel on Climate Change's (IPCC) Fourth Assessment Report (AR4) modeling, but have grown quickly in number since [52] [51] [77]. In the most recent assessment report, AR6, the IPCC stated with strong confidence that CDR will be needed alongside steep emission reductions to meet the Paris Temperature Goal [53] [50]. They define CDR as "Anthropogenic activities removing carbon dioxide (CO_2) from the atmosphere and durably storing it in geological, terrestrial, or ocean reservoirs, or in products".

Smith et al. in *The State of Carbon Dioxide Removal* further define CDR using three core principles [96]:

- *Principle 1: The CO_2 captured must come from the atmosphere, not from fossil sources. The removal activity may capture atmospheric CO_2 directly or indirectly, for instance via biomass or seawater.*

- *Principle 2: The subsequent storage must be durable, such that CO_2 is not soon reintroduced to the atmosphere.*

- *Principle 3: The removal must be a result of human intervention, additional to Earth's natural processes.*

These principles are useful in creating distinctions between CDR and other climate change mitigation actions. Principle 1 helps distinguish CDR from point-source carbon capture (PSC), which focuses on capturing CO_2 at industrial plants that burn fossil fuels. Principle 2 helps differentiate CDR from other short-term carbon removal actions more akin to recycling CO_2, like the use of synthetic fuels made from emitted CO_2 that would immediately be released back into the atmosphere upon use. Principle 3 clarifies that only actions that add additional removal of CO_2 count as CDR. Some argue that CDR should even be labeled completely separately from mitigation techniques in the categorization of climate actions to help with these distinctions, but there is not clear consensus in the literature on this [77].

While it is not a reasonable substitute for deep emission reductions across the globe, CDR can fulfill several roles within the climate change mitigation ecosystem. In the near term, it can help reduce net emissions by offseting emissions as sectors ramp up activities to perform these critical deep reductions. Mid-term, it can help offset emissions from the hard-to-abate sectors, particularly those that have a higher cost for emission reduction than CDR emission offsets to reach global net zero. Long-term, this segment could potentially provide net negative emissions, such that the global net emissions are below zero and can offset historical emission accumulation. [53]

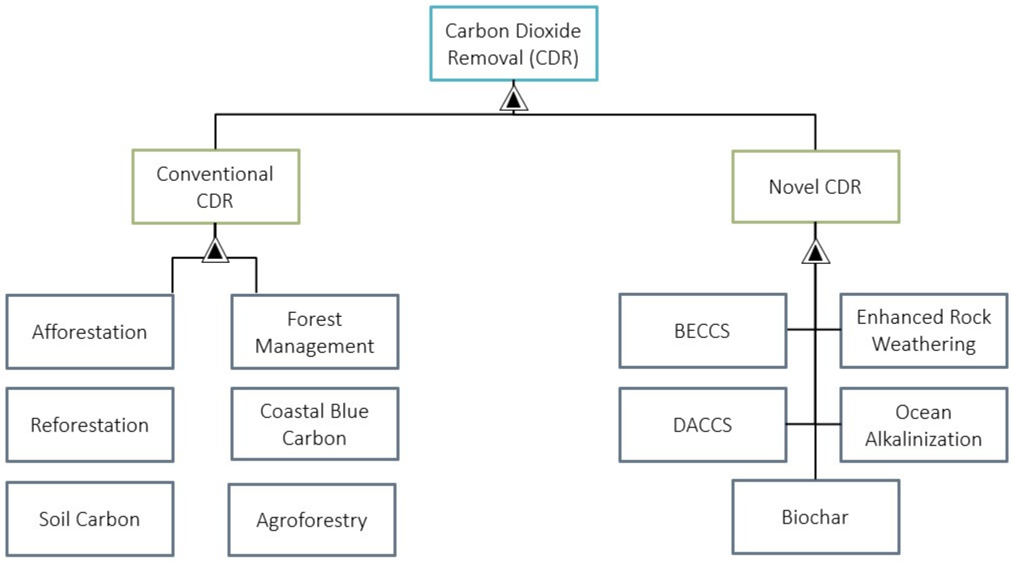

Figure 2.1: Examples of negative emission technologies and their classification within the CDR ecosystem

The technologies associated with CDR are often referred to as Negative Emission Technologies (NETs). There are many different NETs being pursued, ranging from more conventional techniques like afforestation and reforestation to novel techniques like BECCS and DACCS [37]. Figure 2.1 shows some of the most common NET categories for reference. The number of NETs is rapidly growing as this new industry begins to take shape [96]. It is important to recognize that at this time there is no silver bullet approach as each technique has considerable benefits and challenges; instead, a wide portfolio of NETs will be needed to reach the scale of removal needed to support the Paris Temperature Goal [77].

Two critical aspects of CDR when comparing across techniques are (1) the durability of the CO_2 storage and (2) the reliability of monitoring, reporting, and verification (MRV). The scale of durability might range from a few years to hundreds or thousands of years depending on the technique pursued. MRV quality also varies drastically across techniques, but will ultimately be the mechanism for validating if an action should count towards carbon offset or removal goals. The need for MRV governance across techniques has specifically been cited as the most critical need for CDR policy by Smith et al. in the 2023 State of CDR report. [96]

2.1.1 Nomenclature

Due to the large number of CDR techniques under investigation, determining a consistent classification system is helpful. Even within the climate community, however, there is still varying nomenclature used to describe these various groupings of CDR techniques. The Carbon Business Council and over 100 carbon removal experts sent an open letter to the UNFCCC as recently as May 2023 in an attempt to clarify language regarding CDR within an Information Note released by the organization. Within the note, the label "engineering based activities" was applied to several CDR techniques discussed. The letter recommended avoiding this distinction as most CDR techniques are varying degrees of nature and engineering. [14]

Early literature in the CDR domain often defines subclasses as "nature-based" versus "engineered" or "industrial-based" solutions, similar to the nomenclature used by the UNFCCC above. However, caution has been raised against using this classification system since most techniques incorporate some combination of nature and engineering. Some argue that all CDR techniques should just be referred to by their characteristics rather than introducing an intermediate classification system [15]. Others have proposed using the classification system of "conventional" versus "novel" to avoid this conflict [96]. This is a helpful distinction in that it helps clarify between solutions that are very mature and deployed at large scale versus ones that are emerging more recently as the world works to find new ways to combat climate change.

2.1.2 Conventional techniques

Conventional techniques of CO_2 removal make up about 98% of the 2 $GtCO_2$/yr of removals currently in existence [96]. All of these techniques are land-based, and include some of the most well-known and heavily researched removal techniques, like afforestation and reforestation [77]. Other land use and management practices also fall into this category, such as general forest management, restoration of peatland and wetlands (also referred to as coastal blue carbon), soil carbon practices, and agroforestry.

A clear benefit of most conventional techniques is that they are relatively inexpensive compared to novel techniques [77]. Another is that they are generally familiar to the public with an overall positive perception, especially for afforestation and reforestation [96]. The majority of these techniques rely on managing how society uses land and restores specific plant species. They are generally well-understood and many are ready for immediate implementation.

One of the main limiting factors in scaling up these conventional techniques is the value of additional carbon removal versus utilizing that same land for food production. This limitation prevents conventional techniques from being able to scale to a level that can fully cover the level of need for carbon removal. Despite this, it is still expected to make a significant contribution to the CDR portfolio, particularly in the short term as novel techniques scale up. All types of novel techniques are not immune to this same concern regarding land use, but conventional techniques are particularly vulnerable to this sustainability challenge at a certain level of use. [80]

Other challenges with conventional CDR include MRV and durability. Many of these techniques are particularly susceptible to storage reversal if not maintained properly long-term [77]. An example of this would be a tree that is cut down after credit has been taken for CO_2 removal. While there is a large range of reliability across the spectrum of conventional techniques, some have significant challenges with regard to MRV based on current understanding and require additional research [96]. Despite these challenges, these conventional CDR techniques can be very valuable in the short term as more novel, long-duration removal options are scaled up.

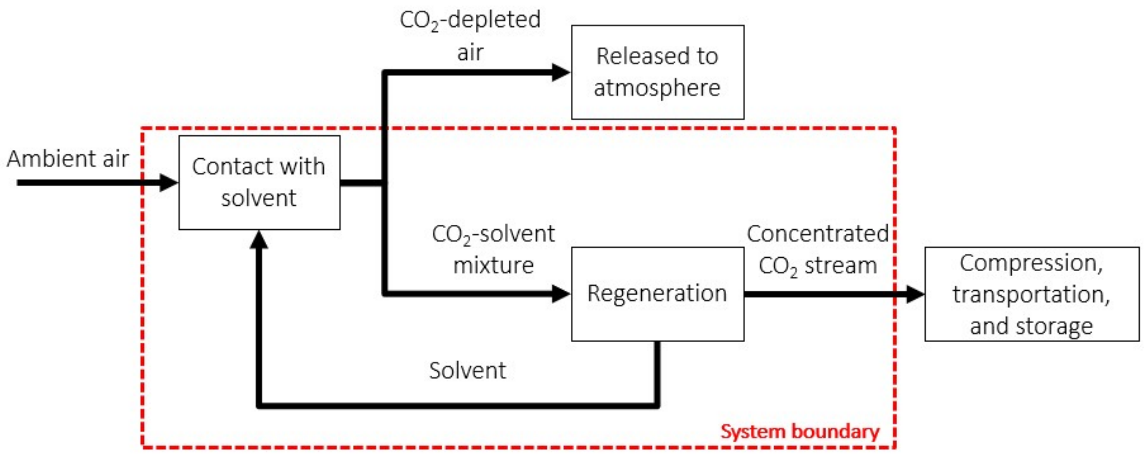

Figure 2.2: High-level process that direct air capture methods generally follow

2.1.3 Novel techniques

Novel CDR encompasses the remainder of techniques being investigated for carbon removal. These techniques currently contribute very little to annual CO_2 removal rates, at about 0.002 $GtCO_2$/yr. It is expected that these techniques will constitute a much larger percentage of the CDR portfolio in the future, as many of these techniques are less constrained by land use than conventional techniques. Examples of techniques that fall into this category include bioenergy with carbon capture and storage (BECCS), enhanced rock weathering, biochar, ocean alkalinization, and direct air capture (DAC). [96]

Due to the large amount of variability of techniques within the Novel CDR group, there are few overarching benefits and challenges that apply to all in the group. In general, many of these techniques have more clear approaches to MRV when compared to Convention CDR, but not all. Many also offer more long-term durability through underground CO_2 storage and mineralization. However, many are not yet ready to be deployed commercially, whether due to high capital costs or the need for additional study. [80]

2.2 Direct Air Capture

Direct air capture is emerging as a CDR technique of particular interest for many companies and CDR buyers [98]. It encompasses a variety of methods that use chemical reactions to pull CO_2 out of the atmosphere that can then be utilized or stored, depending on the application. Since almost half of annual CO_2 emissions are from distributed sources [1], this ability to remove CO_2 from ambient air is particularly appealing to many.

In its most general form, this CDR technique involves pulling ambient air into the DAC system, putting that air in contact with a solvent to draw down the CO_2, releasing the CO_2 through a process called regeneration, then compressing and preparing the concentrated CO_2 for transportation to where it will be stored [36]. This process can be visualized in Figure 2.2. Despite this common overall process, many different methods of DAC are being pursued today by varying solvent types and regeneration processes.

Since land use is one of the key restrictions to many other CDR techniques, it can be helpful to understand DAC's use in comparison. The National Academies of Sciences, Engineering, and Medicine estimate that a 1 $MtCO_2$/yr DAC system removes the same amount of CO_2 on an annual basis as approximately 20 million trees spanning about 100,000 acres [80]. They estimate an average DAC plant of this size at a 65-75% capture rate may require about 6-425 acres of land for the actual plants depending on the configuration, plus an estimated additional 550-25,500 acres for indirect land use and power generation. This land use varies considerably based on the DAC method used and the power source, but more study is needed to understand the realistic range better.

Because they both involve using solvents to extract CO_2 from air, direct air capture and point source capture (PSC) are often confused with one another. However, they differ in a critical way: DAC pulls CO_2 out of ambient air, while PSC captures CO_2 from a specific industrial facility or plant that combusts fossil fuels for energy [8]. This means that DAC can be used as a carbon-negative technology, while PSC can only ever be carbon-neutral at its best [87]. PSC is therefore part of the climate change mitigation portfolio but is not considered a carbon removal technique.

One additional key difference between the two carbon capture techniques is the concentration of CO_2 in the air processed by each system. Depending on the type of power plant or industrial facility the PSC is paired with, CO_2 concentrations range between 3-30%. Alternatively, ambient air that DAC processes target contains just 0.041% CO_2. This means that DAC systems must process significantly more air than PSC systems to remove the same amount of carbon, which can lead to more energy needs and higher costs. [36]

2.2.1 DAC Methods

There are currently many different approaches to direct air capture as a CDR technique. Despite following the general functions of capturing through contact, regenerating CO_2, and storing the CO_2, each method varies the execution form of one or several of these steps. Figure 2.3 shows some of the most common variations for each of these steps along with the relative Technology Readiness Level (TRL) designations. Utilization is greyed out in the Storage Method portion of the figure since current utilization methods do not meet the requirements of a CDR technique for DAC (see Section 2.2.2 for more details).

Within the literature, the various methods are typically named based on their capture method. As shown in the figure, the four overarching methods in development today are Liquid Solvent DAC (L-DAC), Solid Sorbent DAC (S-DAC), Electro-Swing Adsorption DAC (ESA-DAC), and Membrane-Based DAC (m-DAC). The capture method chosen limits the options for regeneration methods based on how strongly the CO_2 is bonded in the capture phase. L-DAC and S-DAC are the two DAC methods that have reached the pilot scale, while the other two are still in the lab phase of development. Both S-DAC and L-DAC are in the process of commercialization and have considerably more literature devoted to their study than other methods. [46]

Three DAC companies in particular are leading in the deployment and commercialization process: Climeworks, Carbon Engineering, and Global Thermostat. There are currently 18 plants in operation across the world, all of which are operated by one of these three companies. Climeworks and Global Thermostat both use variations of the S-DAC method,

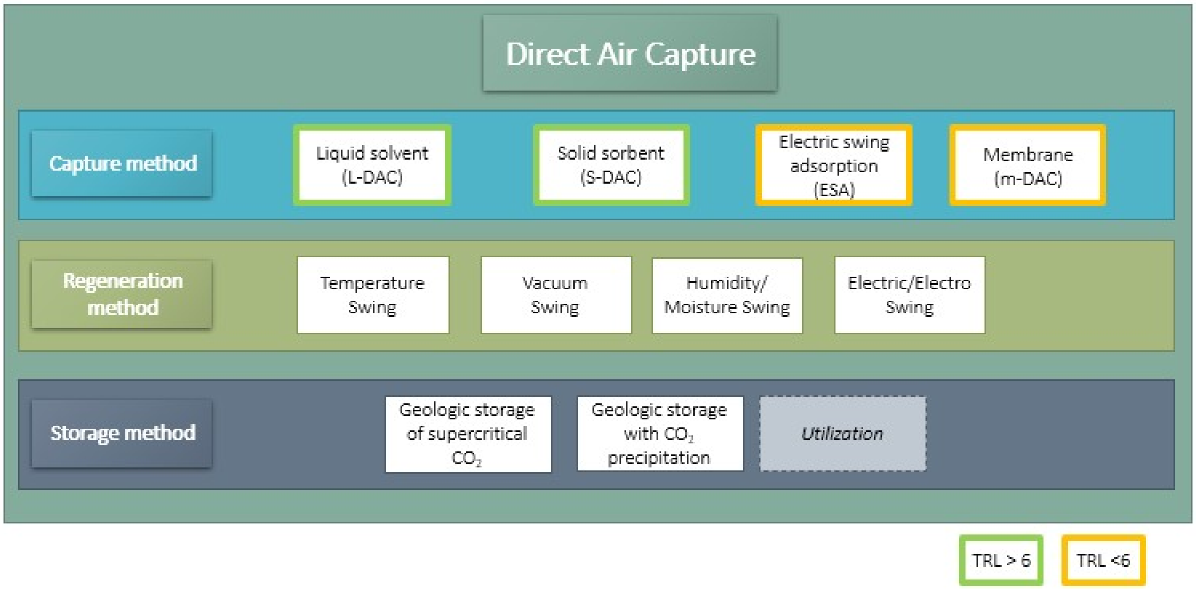

Figure 2.3: Summary of direct air capture methods currently being pursued

while Carbon Engineering uses L-DAC. [47]

Despite these three companies leading in the commercialization space, there are many other companies active in the growing DAC industry. As of July 2023, there are 65 DAC companies that have joined the DAC Coalition, which is likely not inclusive of all in the industry but provides an idea of how quickly the number of companies is growing [21]. Some that publicly share information about their method of capture are listed in Table 2.1, along with their level of maturity and country of origin.

While most in the table are variations of S-DAC, there are a few instances of m-DAC and ESA-DAC. Given the low TRL for these methods, there is still limited information available for these methods [76]. They are still desirable to investigate further despite the immaturity due to the potential for lower energy use, which could ultimately lead to lower DAC costs.

L-DAC

The use of liquid solvents for DAC is a process that has been built off of the existing technology of separating CO_2 from gas mixtures, such as natural gas [97]. These processes have been used commercially for over seventy years in various applications, but the requirement of producing concentrated CO_2 streams for storage from lower concentration gas mixture (ambient air) makes DAC application more complex and costly without additional innovation [37]. Carbon Engineering is the company commercially pursuing this form of DAC, with one pilot plant in operation and the largest DAC commercial plant set to begin operating in 2024 [47]. This plant will have a capacity of 1,000,000 tonCO_2/yr.

L-DAC begins by contacting ambient air with liquid solvents that have a high affinity for absorbing CO_2, such as potassium hydroxide. The solution with the dissolved CO_2 then goes through a series of steps to regenerate the CO_2 as a concentrated stream. It is first precipitated as a solid mixture that enables recycling of the solvent back to the prior stage,

Company	**Location**	**Maturity**	**Method**
Mission Zero Technologies	UK	Founded 2020	ESA-DAC
RepAir Carbon Capture	Israel	Founded 2020	ESA-DAC
Verdox	USA	POC/Pilot in progress	ESA-DAC
Capture6	USA	Founded 2021	L-DAC
Carbon Engineering	Canada	Pilots operating; Constructing commercial facility	L-DAC
Carbyon	Netherlands	Founded 2019; demo	m-DAC
Aircapture	USA	Founded 2019	S-DAC
AspiraDAC	Australia	Founded 2022	S-DAC
Carbon Collect	USA	Prototype constructed (MechanicalTree)	S-DAC
CarbonCapture	USA	Set to operate 2023	S-DAC
Climeworks	Switzerland	Multiple operating pilots & commercial plants	S-DAC
Global Thermostat	USA	Multiple pilots (not operating) and two commercial construction projects	S-DAC
Heirloom Carbon	USA	Founded 2021; successful demonstration	S-DAC
Ifininitree	USA	Operating pilot	S-DAC
Noya	USA	Founded 2020	S-DAC
Removr	Norway	Founded 2022	S-DAC
Skytree	Netherlands	Operating pilot	S-DAC
Soletair Power	Finland	Operating pilot	S-DAC
Sustaera	USA	Founded 2021	S-DAC

Table 2.1: Examples of currently active DAC companies

then it is heated to a high temperature around 900°C with oxygen to release the CO_2 from the precipitant and produce a pure CO_2 stream for compression and storage. The precipitant material can be recombined with water to be recycled to the precipitant step. Due to the strong bond between the CO_2 and the precipitant, L-DAC is generally only paired with the temperature-swing regeneration technique. [32]

There are several benefits and challenges unique to L-DAC. It can be run continuously and at large scales, which can be beneficial for economies of scale capture. However, due to the high temperature needed for regeneration, it currently requires natural gas combustion as an energy source, which emits more CO_2 that must be recovered or accounted for in the total net CO_2 removed calculation. This method can also have heavy water usage requirements depending on the ambient conditions at the plant location. [47]

S-DAC

As shown in Table 2.1, the majority of companies in the DAC industry are currently focused on variations of S-DAC [8]. This is a less mature DAC process compared to L-DAC and has more space for quick learning and innovation that could drive cost reductions [47].

In solid sorbent DAC, ambient air is drawn into the system and contacted with a solid sorbent that adsorbs the CO_2. The regeneration phase can then begin, where the mixture undergoes heating at low temperatures of around 100°C or less, pressure changes, humidity changes, or some combination of these to regenerate the sorbent and release the concentrated CO_2. Since the process uses adsorption instead of absorption, a weaker bond is created between the CO_2 and the sorbent, allowing for more regeneration options and lower temperature requirements compared to L-DAC. [32]

Similar to L-DAC, S-DAC faces unique benefits and challenges. Due to the lower temperature requirements, it is more easily paired with renewable or low-carbon energy for electricity and thermal requirements. Rather than using water for operations, some forms of S-DAC can actually produce water as a by-product which may be beneficial in some communities. The size of S-DAC units can also be relatively small, allowing for modularization and a larger range of applications. However, sorbent costs are very high and the units cannot run continuously as each must individually cycle between capture and regeneration. [47]

Climeworks is the leading commercial company utilizing a form of S-DAC, with 15 DAC plants across the world that have capacities ranging from 3-4,000 $tonCO_2/yr$ [47]. The 4,000 $tonCO_2/yr$ plant, Orca, achieved third-party verification of its DAC carbon removal process in January 2023, which was a first for the DAC industry [7]. It is currently the only company offering carbon removal through DAC as a product [47].

Emerging DAC Technologies

Two alternate DAC methods that are being investigated include ESA-DAC and m-DAC. Both are still in the laboratory level of study but could provide future opportunities for DAC if successful [47].

Electro-swing adsorption uses an electrochemical cell for the separation of CO_2 from air. When ambient air is contacted with the negatively charged electrode within the cell, the

CO_2 is adsorbed. A positive charge is then applied to release the CO_2, which can then be compressed and prepared for storage. [105]

The ESA-DAC technology has been shown to be more energy efficient than the traditional DAC methods in higher CO_2 concentration streams but has only yet been proven at lab scale down to concentrations of 0.6%, which is not quite as low as outdoor ambient air [47]. The method also faces unique challenges specific to electrochemical systems that must be addressed before it is ready for commercial scale [6]. However, several companies and researchers are actively pursuing this method. If successful, ESA-DAC could deliver a less energy-intensive, very modular alternative to the more mature DAC methods.

An even less mature DAC method is m-DAC. It involves the separation of CO_2 through the use of multiple stages of separation via membranes [30]. Keith et al. argue that this method is generally impractical due to the force required for membrane use at such low concentration of CO_2 in ambient air [61]. It is still a method being actively studied for point-source capture use since this application has a higher CO_2 concentration. Any breakthroughs in PSC application could initiate future DAC innovations [47].

2.2.2 Storage vs. Utilization

Once the CO_2 is separated out from the ambient air, something must be done with it. In current DAC workflows, this means either storage or utilization. Either option has potential upsides and drawbacks.

Carbon utilization has the benefit of creating immediate monetary value for the extracted CO_2. Examples of utilization options include use in carbonated beverages or greenhouses, the creation of high-quality concrete, enhanced oil recovery, and the creation of synthetic fuels. The current drawback to utilization is that, at least in its current state, it is essentially CO_2 recycling at best, rather than actual CO_2 removal, except in the case of long-duration storage in concrete. Most utilization methods release the carbon back into the atmosphere within a short time period. Utilization will likely be instrumental in bringing down the cost of direct air capture as a technology, as it will be the primary way to make companies in the industry profitable until the cost of DACCS approaches buyer willingness to pay for carbon removal. [87]

Storing the carbon instead of using it is a much more durable practice and therefore qualifies as carbon removal. It is most commonly stored either in its supercritical state underground through a process called sequestration or stored as a solid by injecting it as a liquid solution into basalt or other reactive rocks, which is sometimes referred to as carbon mineralization. Because these processes can store carbon so effectively for massive time scales, they are often referred to as permanent removal methods. [80]

2.2.3 Barriers to Implementation

The critical barrier to utilizing DAC is deftly summarized by Howard Herzog in his book *Carbon Capture*: "The question for DAC is not whether we can suck CO_2 out of the air, but whether we can do it economically on a large scale" [37]. Multiple methods exist that can successfully complete the goals of DAC today as described in Section 2.2.1, but they are at such high costs that they are not economically competitive for carbon removal.

This high cost is primarily driven by the significant amount of energy required for operation, particularly the thermal energy in the regeneration stage [80]. The cost of sorbent materials for S-DAC can also involve massive capital expenditures, especially if they have a short lifetime [76]. While improvements in cost are likely as experience and learning grow, the energy requirements set by thermodynamics will set a cost floor for the technology given the current methods [36].

Other barriers include materials use, land use, humidity challenges in certain areas, and water use. Water use varies by DAC method since some S-DAC technologies can actually produce water. Land use impacts are lower compared to many other land-based CDR techniques, but still worth considering especially if onsite power systems are utilized. Indirect land usage should also be considered, as specific spacing between units may be required for optimal operations. Concerns have also been raised around the impact of low levels of CO_2 near large facilities on crops and local ecosystems. [80]

The flexibility in location for DAC plants is often cited as a key benefit of DAC, but permitting and access to locations near underground storage could still create challenges [36]. Cooperation and engagement with local communities can help ease some of these challenges, but it is something to consider as operations are scaled up.

Despite these barriers, according to the IPCC DACCS faces the fewest constraints other than its cost compared to all other known CDR techniques [53]. Bringing down the costs of this technology will be critical for its successful deployment for carbon removal.

2.2.4 Larger DAC Market Ecosystem

As recognition from the IPCC that CDR will be necessary to meet the Paris Temperature Goals has grown, the energy around DAC and its potential contribution to the CDR portfolio has escalated. This section provides a high-level overview of the current ecosystem through the lenses of public policy support, private sector purchases, and the DAC providers themselves. This ecosystem will be a key component of understanding potential future DAC costs.

Public Policy Support

According to the IEA, Canada, the European Union, the United Kingdom, and the United States have taken the lead in supporting DAC across the spectrum of development, from early R&D to demonstration and deployment [47]. While other countries are also providing support, these four have the most extensive policies in place.

The U.S. has passed two pieces of legislation since 2020 that are specifically beneficial for DAC development. The first is the Infrastructure Investment and Jobs Act (IIJA), otherwise known as the Bipartisan Infrastructure Law, in 2021 [101]. This bill commits \$3.5 billion toward the creation of four DAC hubs within the US, along with an additional \$115 million in funding for pre-commercial and commercial DAC prizes. The second critical bill is the Inflation Reduction Act (IRA), which changed the tax credits associated with Section 45Q of the Internal Revenue Code [45]. The passage of this legislation increased the tax credit for DAC with underground storage in saline formations from the prior amount of \$50/tonCO_2 to

\$180/tonCO_2 and also adjusted the capacity requirements for DAC tax credit qualification from 100 MtCO_2/yr to 1 MtCO_2/yr.

Additional policy progress is being made in the U.S. at a more local level. California, New York, Massachusetts, and Maryland are leading in general CDR policies and taking a portfolio approach that can be inclusive of DAC [74]. The California Low Carbon Fuel Standard (LCFS) law in particular allows DAC projects anywhere globally to receive traded credits on average of \$200/tonCO_2 as long as they meet the standards of the program [47] [11]. This credit can be combined with the 45Q credit for DAC projects that meet the requirements of both programs. When looking across states, DAC is noted as the technology most preferred by states for R&D funding [74], likely due to the DAC hub program.

Globally, DAC policies are also growing. While this thesis will not go into specific laws globally, what is important is that CDR and CCUS policies, and DAC eligibility by extension, have hundreds of millions of USD equivalent funding across the development process in at least four countries. Some laws focus solely on DAC, while others are just inclusive of the technology with funding or credits for DAC methods that meet the requirements. [47]

Private Sector Purchasers

Since 2020, DAC companies have raised around \$125 million in investments [47]. Despite the growing government funding support globally, the private sector is also becoming active in DAC investment.

In 2020, the company Stripe announced that it had prepurchased 322.5 tonCO_2 of Climeworks's DAC with storage carbon removal for \$775/tonCO_2 [85]. By 2021, Shopify [17] and Microsoft [18] had also announced commitments to purchase carbon removal through Climeworks. The three joined together with Alphabet, Shopify, Meta, and McKinsey in 2022 to launch Frontier, an Advance Market Commitment (AMC) focused on accelerating permanent carbon removal technologies with a \$1B commitment through 2030 [28]. The group expanded to include Autodesk, H&M Group, JPMorgan Chase, and Workday a year later, adding another combined \$100M to the fund [29]. Since its launch, the AMC has purchased from fifteen CDR startups, four of which focus on direct air capture.

The idea behind an AMC is to encourage the development of a product by signaling a demand where supply is lacking. It was first used to stimulate the development of vaccines for low-income countries in 2007 [66]. In 2021, Athey et al. wrote an opinion article in Politico recommending a similar action be taken for CDR to expand the available portfolio [2]. The Frontier AMC was launched a few months later with this goal.

The Frontier AMC is not the only player private sector currently supporting the growth of the DAC industry. For example, the Climeworks website lists seventeen companies that have entered long-term commitments with the company for carbon removal services as of July 2023 [19]. Other companies are investing in the technology, often through DAC with utilization rather than storage. Others are partnering directly with DAC companies to advance deployment, like Oxy Low Carbon Ventures and Carbon Engineering [73].

The willingness of Frontier and other early purchasers to pay for DAC at its current costs could help bridge the gap between high prices and the policy support mechanisms, like the 45Q tax credit and LCFS in the U.S. Alongside niche applications of DAC with utilization, these early commitments are helping to create an early market for DAC and could help drive down costs to a level that additional CDR purchasers can afford [47].

DAC Providers

An overview of the technical DAC methods of the most active DAC providers is included in Table 2.1 from Section 2.2.1. The list of DAC companies is continuously growing as the demand from governments and the private sector continues to rise. The U.S. in particular is seeing a large growth in companies founded since the passage of the IIJA and IRA laws. As more players enter the field, the larger the opportunity for improvements of the various DAC methods grows through knowledge sharing and competition across companies.

2.2.5 Cost Reduction Predictions

Experts have been debating whether or not direct air capture will come down in cost far enough to be economical for decades [25]. In 2011, House et al. predicted the costs would be around \$1,000/tonCO_2 for net removal [38]. The American Physical Society released a highly influential study that same year estimating \$780/tonCO_2 avoided for their "realistic" case, including emissions from powering the facility [97]. Since then, many experts have studied the potential cost of this technology, predicting costs ranging from \$100/tonCO_2 to \$1,000/tonCO_2 still [47].

Many studies are focused on eventual DAC cost, rather than initial costs that come with first-of-a-kind (FOAK) plants. However, a few studies do look at both. Fuss et al. estimate FOAK plant costs to be in the range of \$600-\$1000/tonCO_2 based on their extensive literature review in 2018 [31]. Keith et al. provide detailed cost estimates for an L-DAC FOAK plant in the range of \$168-\$232/tonCO_2 (2016\$) based on Carbon Engineering's design [62]. Initial costs for S-DAC are more straightforward, as the reported price for Stripe's carbon removal purchase through Climeworks is \$775/tonCO_2 [85]. Climeworks's cost of \$600/tonCO_2 is sometimes referred to in the literature, but this is based on gross removal, not total net removal [36]. Boston Consulting Group released a study as recently as June 2023 in which they estimate FOAK costs for L-DAC as \$880/tonCO_2, S-DAC as \$1,705/tonCO_2, and ESA-DAC as \$1,415/tonCO_2 [3].

The same Boston Consulting Group report shows dramatic cost reduction potentials for each of the technologies: L-DAC as low as \$100/tonCO_2, S-DAC as low as \$70/tonCO_2, and ESA-DAC as \$95/tonCO_2 [3]. In the 2019 report on negative emission technologies, the National Academies of Sciences, Engineering, and Medicine estimate a range of costs between \$156-\$506/tonCO_2 for a generic L-DAC system and a range of \$89-\$407/tonCO_2 net for S-DAC using various energy sources[1] [80]. Fuss et al. provide an estimate of nth plants of \$200/tonCO_2, with a full range of costs from \$100-\$300/tonCO_2 [31]. Keith et al. also provide detailed cost estimates for nth L-DAC plant designs in the range of \$94-\$170/tonCO_2 [62]. Climeworks reports having a roadmap of how they will reach \$200/tonCO_2 removal costs by 2025 for their S-DAC design [33].

A concern raised by Howard Herzog and others is that often cost estimates for DAC are on a gross removal basis, rather than a net CO_2 removed since the DAC process usually

[1] Excludes the scenario that utilized coal as an energy source for S-DAC since this method is not usually paired with coal.

involves some energy use that is not carbon-emission free [36] [76]. This can be tricky when comparing across estimates when gross vs. net is not specified. All costs reported in this section are for net removal costs upstream of compression, transportation, and storage unless otherwise noted.

2.3 Technological Progress Estimation

With the introduction of any new technology, there is usually a desire to understand how the costs will change over time. For a technology like direct air capture whose primary barrier to commercial growth is cost, this desire is particularly strong. The theory of technological change is one approach used extensively across the literature to forecast this behavior, especially for energy-related systems [4] [56] [75] [81]. While there are multiple approaches to estimating cost reductions for technologies within technological change theory, two stand out as the most common: 1) the use of Wright's Law which attributes cost changes to cumulative experience [108] [109] and 2) the use of Moore's law which attributes those changes to the passage of time [5] [24] [64].

Most studies tend to focus on one approach or the other, but in 2013 Nagy et al. completed a study comparing the accuracy of these two approaches against each other and four others [79]. Their study suggests that both Wright's and Moore's approaches demonstrated similar performance, with Wright's Law being the stronger of the two. Their findings support the proposal from Sahal that Moore's Law and Wright's Law become equivalent when cumulative experience grows exponentially [91]. Nagy et al. note that within the database they used for the comparison of approaches, the majority of technologies do exhibit this exponential growth [79]. Therefore, their conclusions may not be applicable to technologies that do not see exponential experience growth.

2.3.1 Learning Rates

In 1936, Thomas P. Wright first introduced the concept of the learning curve [106]. He observed that there was a relationship between the number of units of a Boeing aircraft manufactured and the number of manhours it took to manufacture each unit. This phenomenon is referred to across the literature by many names, most commonly by learning rates, experience rates, progress functions, and learning-by-doing.

While Wright's observations centered around manufacturing and labor hours, the idea he proposed has evolved and been used across many industries [91] [109]. It is now recognized as the most common and most research-supported approach for estimating technological cost reductions [100]. For energy-related technologies, it has frequently been used to relate cost reductions to installed capacity or production as an estimate of cumulative experience [57] [59] [108]. Equation 2.1 shows the classic formula for this application:

$$Y = ax^b \tag{2.1}$$

where Y is the unit cost of the technology at a given time, a is the unit cost of the first unit, x is the cumulative experience, and b is the rate of the cost reduction. The learning rate (LR) is determined by b as shown in Equation 2.2:

$$LR = 1 - 2^b \tag{2.2}$$

where LR is the learning rate. The progress ratio (PR) is also often regularly reported in the literature, which is shown in Equation 2.3:

$$PR = 1 - LR \tag{2.3}$$

Equation 2.4 is an adapted version of Equation 2.1 that relates the cumulative experience to the capacity installed at a current time relative to time zero. Since cumulative installed capacity is the most common way of representing experience for energy technologies [16], this form of the equation is seen frequently across the literature:

$$C(x_t) = C(x_0)\left(\frac{x_t}{x_0}\right)^b \tag{2.4}$$

where C_{x_t} is the cost of the technology at a given time, C_{x_0} is the initial cost, x_t is the cumulative installed capacity at time t, x_0 is the cumulative installed capacity at the start of the analysis, and b is the rate of cost reduction as described in Equation 2.1.

The equations listed are the single-factor or one-factor approach of learning curve use. However, there are many other versions of learning rate analysis used across the literature. While one-factor models are the most common, the most common multi-factor approach seen in the literature is the two-factor approach. This approach uses both learning-by-doing and learning-by-research rates independently of one another, then sums the combination of the two to find the overall learning rate. An even more detailed analysis approach is the component approach. Both of these will be discussed in more detail in Section 2.3.3. [89]

Despite the regular use of learning curves for energy technologies, there is a considerable amount of caution provided by experts for use. For example, Junginger et al. point out that deciding the appropriate boundaries for analysis can drastically change the results found by learning rates like the time period of study, geographical boundaries, and other financial factors [57]. Another issue often argued is the necessity to include a cost floor for learning curve analyses to ensure costs don't fall unreasonably far for a given technology [75] [65] [90].

One key consideration when using experience curves is deciding what to use as the starting point for the analysis. This can be particularly tricky when applying analog historical learning curves to relatively new technologies since it has been observed that costs often increase rather than decrease in the early commercialization stage of deployment for new technologies [90] [9]. This time period before learning curves are applicable is often referred to as the pre-learning phase. To account for this, academics sometimes utilize an assumed cumulative capacity that must be reached before learning begins [4] [90]. In contrast to this, Ferioli et al. suggest that ideally, the analysis start point would be at production time zero [27]. However, they do note that it is often more practical to choose the start of the analysis based on current cumulative production instead.

Another similar but different criticism of early learning curve periods is that initial small capacities scaling up quickly can result in excessive price drops over a single year if learning curves are applied blindly. Kouvaritakis et al. address this issue by applying a cap on any single-year cost reduction [65]. Overall, there is no consensus in the literature on how to handle the start of learning curve analysis. It is apparent, though, that this should be a key consideration when undergoing a new analysis.

Despite most technologies experiencing a positive learning rate, negative learning rates are possible. This occurs when prices increase over time for a technology, rather than the typical reduction. Reasons for this specifically in energy technologies have been attributed to oligopolistic behaviors [65], costly regulatory restrictions [56], and experience depreciation over long periods of time if facilities are built less regularly [75].

2.3.2 Improvement Rates

Rather than basing the rate of cost reduction on cumulative experience, improvement rate calculations simplify things by relating the cost reduction to time. This was first proposed by Gordon E. Moore in 1965 when he predicted that every two years the number of transistors on integrated circuits would double [78]. Equation 2.5 shows the accompanying formula for the observation, today known as Moore's Law [79]:

$$Y = B * e^{-mt} \tag{2.5}$$

where Y is the unit cost of the technology at some time, t, B is the unit cost at time zero, and m is the improvement rate.

Using Moore's law simplifies cost reduction estimates dramatically compared to learning rate analyses since the assumptions on how much experience is gained over time are removed from the calculation. It has been expanded upon and extended to other technologies since Moore's original observation, such as energy technologies. Christopher L. Magee in particular has worked with many coauthors using patent analysis combined with Moore's law to estimate technological improvement for various energy technologies [5] [26] [95].

While not as common in the literature for energy technologies as learning rate analyses, improvement rate analyses can still provide insight into how technology costs are changing over time. It is yet another lens through which technological progress can be viewed to get a better overall picture of potential change paths.

2.3.3 Multi-Factor Approaches

One key criticism of one-factor learning rate analyses is that they assume learning-by-doing is the only effective driver of cost reductions being estimated [93]. Because of this potential oversimplification, it has been suggested that one-factor models are often more optimistic than reality [70]. Multi-factor technological change models attempt to address these concerns by including more detail in the analysis.

Two-factor analysis is one multi-factor analysis approach that addresses this concern. It is one of the most common multi-factor analysis approaches seen across the literature for energy technologies [56] [89]. This approach typically includes one learning-by-doing factor and another learning-by-research factor focused on R&D spend over time [65]. Two key criticisms of this approach include the reliability and availability of data on R&D spend in both the public and private sectors and the interconnections of these two variables [108].

Another multi-factor approach that avoids these concerns is the component-based approach. This approach simply expands the traditional learning curve formula to include a factor for each component within a system decomposed to some level chosen by the researcher, then sums the subsystems to understand the system level [27] [108]. By approaching the problem in this way, the analysis can account for different levels of maturity and complexity for the components that make up a technology [89]. It also has been suggested to help explain why learning curves often seem to flatten over time, as some components may mature faster than others [27]. Equation 2.6 shows this application to 2.4:

$$\begin{aligned} C(Q_t) &= \sum C_{0i}\left(\frac{Q_{ti}}{Q_{0i}}\right)^{-b_i} \\ &= C_{01}\left(\frac{Q_{t1}}{Q_{01}}\right)^{-b_1} + ... + C_{0n}\left(\frac{Q_{tn}}{Q_{0n}}\right)^{-b_n} \end{aligned} \tag{2.6}$$

where $C(Q_t)$ is the total cost of the technology at a given time t, C_{0i} is the initial cost of each component i, Q_{ti} is the cumulative installed capacity at time t of each component, Q_{0i} is the cumulative installed capacity for each component at the start of the analysis, and b is the rate of cost reduction as described in Equation 2.1.

This same idea can also be applied to improvement rate estimations. Equation 2.7 shows the multi-factor version of Equation 2.5 for this use:

$$\begin{aligned} Y &= \sum B_i * e^{-m_i t} \\ &= B_1 * e^{-m_1 t} + ... + B_n * e^{-m_n t} \end{aligned} \tag{2.7}$$

where each variable of Equation 2.5 is now expanded into each component i.

Similar to other approaches for estimating technological progress, the component approach does have criticisms within the literature. It struggles with accurate information at the right level of detail as discussed for two-factor approaches [89]. The concerns raised with early learning and other uncertainties noted in one-factor analyses can also be applied at a component level with this approach, such that the overall uncertainty in the results is potentially higher upon aggregation [108].

2.3.4 Application to Direct Air Capture

Learning curves have been utilized for estimating direct air capture costs by several researchers, with many different interpretations of appropriate analog rates. In 2012, Nemet and Brandt proposed using learning rates of 10% from carbon capture at power plants for DAC as the closest analog [83]. Fasihi et al. directly refute this proposal in 2019, saying it is more appropriate to use a learning rate of 15% due to DAC's high modularity [25]. They point out that similar modular energy technologies see averages in this range as there are more opportunities for standardization at an international level and massive economies of scale. Breyer et al. support this, citing a range of 10%-15% as realistic [8]. Azarabadi and Lackner choose a rate of 20% for their DAC learning rate analysis, citing solar PV, fuel cells, and electrolysis as analogs in both their 2020 and 2021 economic assessments [4] [67].

Finally, McQueen et al. use the full range of 10%-20% for their 2021 analysis specifically for S-DAC costs to understand the range of outcomes for this method [76].

From these papers, some similarities can be noted. First, all use learning rates for their analysis; none found focus on improvement rates. All but Nemet and Brandt focus on one-factor analysis for DAC, while they investigate a component approach using three factors: capital cost, energy cost, and O&M cost [83]. Only McQueen et al. specified which DAC method their analysis was focused on. While most provide context around why a given learning rate is chosen, this component of each analysis is not described in much detail.

Considering these gaps in the literature, this thesis aims to analyze the potential future costs of DAC through several lenses. First, an analysis is conducted to better understand an appropriate analog technology for each of the most common DAC methods. Then these results are used to perform one-factor LR and IR analyses and component-based LR and IR analyses for both S-DAC and L-DAC methods. This allows for comparison across estimation approaches for each DAC method and for comparison across DAC methods.

Chapter 3

Method and Framework

This chapter first describes the approach used to answer the research questions identified in Section 1.3. It then compiles the necessary inputs for the learning and improvement rate analyses. These inputs include initial DAC cost estimates, DAC's anticipated experience growth rate, the system decomposition by DAC method, and the key drivers for each analog technology considered for comparison to DAC methods in Chapter 4.

3.1 Problem Formulation

As described in the Literature Review, while there are many ways to estimate how the cost of a given technology may reduce over time, the most common approaches are using Wright's law for learning rates or Moore's law for improvement rates. While the literature shows that either approach should yield similar results in the short term [79], this thesis uses both approaches to explore the range of probable outcomes for DAC cost reductions through two lenses: one-factor learning/improvement rate analysis and component-based learning/improvement analysis.

The estimation of the cost reduction using Moore's law is relatively straightforward since time is the independent variable utilized. Key inputs include the improvement rate and the initial cost, as described in Section 3.2. It is worth noting that the availability of improvement rate data is somewhat scarce and only available for some analogs being assessed. This is discussed further in Section 3.2.4.

Using learning rates for cost reduction estimation adds complexity to the analysis by requiring an estimate of DAC experience over time if the results are to be compared to the Paris Temperature Goal. Assumptions for this portion of the analysis are described in Section 3.2.2. Other key inputs include learning rates and initial cost, which are described in more detail in Section 3.2. Learning rate estimates are very common for all analog technologies being compared and have been well summarized by key papers utilized for the analysis.

3.1.1 DAC Methods Considered for This Assessment

Before beginning the analysis, the scope boundaries must be defined. The first of these boundaries is the methods of DAC to include for evaluation. Within the relatively young

DAC industry, a dominant design has not yet emerged [46] [31]. As seen from the literature review, there is still a wide range of methods being investigated and pursued. Therefore, the range of assessment for this thesis has been limited to several of the most common approaches: S-DAC, L-DAC, ESA-DAC, and m-DAC. All four will be assessed in the analog analysis, but only S-DAC and L-DAC will be investigated in the cost reduction analysis.

While the CO_2 captured by DAC systems can be utilized or stored, the scope of this analysis will focus solely on pairing DAC with storage. While DAC with utilization will likely be a key enabler for bringing down the cost of DAC systems overall through niche markets, most applications for utilization at this point are carbon neutral rather than carbon negative since they are not storing the CO_2 for a long duration [54] [82] [87] [98]. This analysis is focused on the cost of DAC when used as a carbon removal technology and will therefore consider the cost of sequestration as part of the calculations.

3.1.2 Framing of DAC Analog Analysis

The analog analysis investigates several energy technologies that have had enough technological change over time to infer a learning or improvement rate. Through the literature investigation in Section 3.2.4, drivers for each technology's rate of change are identified. These are crucial inputs for the one-factor learning/improvement rate analysis and also help provide context within the component-level analysis.

Once identified, these drivers are compared against the four DAC methods to determine an appropriate analog for each in Section 4.1. The learning and improvement rates for each analog can then be used to estimate how one may expect the cost to change over time for the two most mature methods: S-DAC and L-DAC. It also helps identify levers that governments and DAC providers could utilize to help accelerate cost reductions moving forward. This will be discussed in more detail in Chapter 5.

Since ESA-DAC and m-DAC do not yet have pilot-scale operations, these technologies are not included in the cost reduction analysis. Instead, these DAC methods are included in the analog analysis to support future studies. Their inclusion in the analog analysis also provides insight into opportunities for companies to consider to enable future cost reductions through early architectural decisions.

3.1.3 Framing of DAC System Decomposition Analysis

The system decomposition approach breaks down DAC technology into subsystems for more detailed cost reduction forecasting. This enables the analysis to capture variance in cost reduction forecasts at the component level, since different components of the system may be at varying levels of maturity. The methodology utilized for this analysis closely follows that of Rubin et al. for the application of point-source CO_2 capture [90]. The DAC systems are decomposed into subsystems, a learning rate is applied to each, then the cost of the total system is calculated based on the sum of the subsystems. A typical learning curve can then be applied to this result to directly compare the total system cost to that calculated from the one-factor analysis.

Due to data availability, only the two most mature DAC methods are investigated using this approach: S-DAC and L-DAC. Since both have reached pilot-level operations, significantly more information on how these systems integrate together and their approximate costs is available for assessment.

It is worth noting that the lack of inclusion of the other DAC methods in the decomposition assessment does not indicate that these methods will not be key contributors to DAC as a net negative technology in the future. In fact, if some of these methods can be implemented at a commercial scale, they could be instrumental in bringing DAC down the cost curve by utilizing less energy-intensive carbon removal techniques [94] [105]. However, given the limited amount of detailed information available for these methods in the literature at this time, it is most effective to consider these only for the analog analysis.

3.2 Inputs for Analysis

Several key inputs must be compiled to complete this analysis. The first is an initial cost assumption for the DAC methods in scope. Next, future DAC capacity scale-up assumptions are described as an approximation of experience to perform the learning rate analyses. A system decomposition for DAC to be utilized in the component learning and improvement analyses is then devised. Finally, evaluation criteria for the analog analysis are developed.

3.2.1 Initial Cost Estimates

As discussed in Section 3.1, only S-DAC and L-DAC are considered for cost reduction analysis since they are both mature enough for robust current or actual cost estimates. All calculations will assume 2024 as the starting year for the analysis. Cost estimates vary drastically between the two methods due to very different system materials and processes. Therefore, each will have a different initial cost assumption based on the existing commercial operations and literature estimates. It is also worth noting that much of the literature is focused on eventual capture costs for nth systems, not necessarily initial first-of-a-kind (FOAK) costs. This distinction is carefully considered for this choice of initial estimates.

As Climeworks is the only S-DAC company with commercial CDR operations, their reported price for Stripe's carbon removal purchase of \$775/tCO_2 is utilized [85]. Since this price includes both capture and storage, the storage portion of the price is removed for this analysis since it is solely focused on the price of CO_2 capture. The approximate price of CO_2 storage with Climework's storage partner, Carbfix, on their website is listed as \$25/tCO_2 [13]. This puts the initial price of S-DAC for the analysis at \$750/tCO_2.

L-DAC does not yet have commercial operations, but detailed cost estimates are available in the literature. Keith et al. explored the cost of this method in detail and found that a range for initial costs of \$168-\$232/tCO_2 (2016\$) is appropriate for a FOAK plant based on Carbon Engineering's baseline process and pilot operations [62]. In a more recent study that breaks down DAC costs by method and components, the National Academies of Sciences, Engineering, and Medicine report a range of \$156-\$506/tCO_2 for a generic L-DAC system's net removal cost across a range of energy sources; however, this study does not specify if these cost ranges are for FOAK or nth plant assumptions [80]. The large range of costs can be attributed to the variation of emissions across the energy sources included in the study and the associated cost to capture the additional carbon emissions, plus a variance of price quotes and sources for the components that make up the system. Regardless of whether they are looking at initial or final costs, this range has estimates that exceed the Carbon Engineering prediction. Considering the full range of costs across the literature for this method, an L-DAC average initial capture cost is chosen at \$330/tCO_2 for this thesis.

Since these initial cost estimates are using reported CO_2 purchase amounts, these are technically prices and likely include some inherent margin. However, price and cost will be used interchangeably throughout the thesis for readability.

3.2.2 DAC Experience Growth

To perform the portion of the analysis that uses learning rates, assumptions must be made regarding how DAC experience will grow. For energy technologies, this is usually approximated through cumulative capacity growth [75]. For the base analysis, the "CO_2 capture by direct air capture 2020-2030" dataset compiled by the International Energy Agency (IEA) is utilized [40]. The "Operating capacity" and "Advanced development" project capacity estimates are summed and extrapolated to 2050 as the baseline global capacity growth trend.

The total global capacity is considered to be evenly divided between S-DAC and L-DAC for this analysis. This is based on the existing breakdown of projects in IEA's database [40]. While more companies in the industry are focused on S-DAC methods, L-DAC system capacities are much larger such that the overall project capacities between the two methods are split fairly evenly in the planned project list.

It is worth noting that this may be a relatively conservative DAC capacity forecast as it only considers projects far into development and currently operating; however, it provides a strong baseline for cost reduction expectations. For this reason, several capacity growth sensitivity cases are also considered in the analysis with varying degrees of DAC implementation. Some focus on what could be expected based on announced projects while others focus on what would be needed to meet the Paris Temperature Goal. Table 3.1 outlines these additional sensitivity cases. Figure 3.1 shows how the scaling rates compare to one another for reference, excluding the analog scale-up rates since those will be chosen in Chapter 4. Announced project extrapolations are noted by squares, while goal-derived forecasts are indicated by diamonds. The total UK emissions from 2022 are also shown in Figure 3.1 for reference of the scale of removal capacity compared to actual emission levels [88].

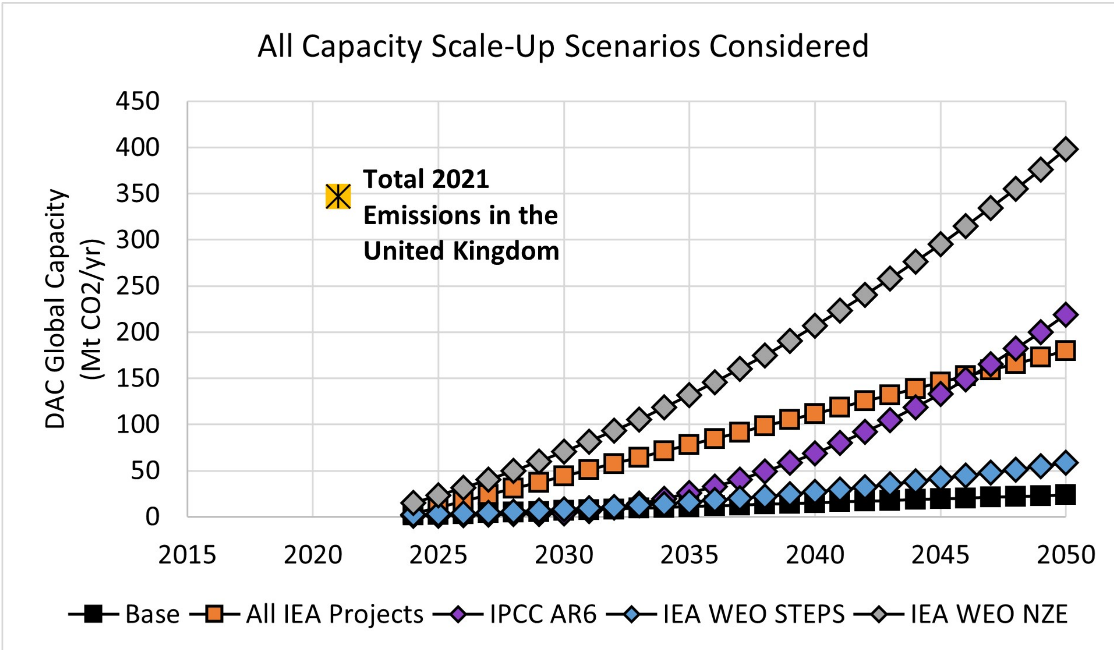

Figure 3.1: Plot of DAC capacity scale-up scenarios considered

Case	Description	Source
Base	Projection: Projects in IEA's DAC Projects dataset listed as operating or in advanced development	[40]
Analog Scale-Up	Projection: Assumes DAC capacity scales at the same rate as the chosen analog for LR analysis	[23]
IEA All Projects	Projection: Base scenario plus the IEA-identified early development projects	[40]
IPCC AR6	Goal-derived: Average of DAC capacity across AR6 scenarios that meet the Paris Temperature Goals (C1-C3 scenarios)	[10]
IEA WEO STEPS	Goal-derived: DAC capacity from IEA's World Energy Outlook Stated Policies scenario	[48]
IEA WEO NZE	Goal-derived: DAC capacity from IEA's World Energy Outlook Net Zero Emissions scenario	[48]

Table 3.1: DAC capacity scale-up scenarios considered

3.2.3 DAC System Decomposition

For the component analysis, each DAC system is broken down into smaller components with an individual learning or improvement rate due to the assumption that some system components will have a cost change more rapidly than others. First, the systems are split into capital expenses (CAPEX), operating expenses (OPEX), and costs associated with capturing the generated emissions from operating. Then the systems are further divided into components based on function within the capture process.

Cost assumptions for each component system are based on the DAC techno-economic analysis in the *Negative Emissions Technologies and Reliable Sequestration: A Research Agenda* report from the National Academies of Sciences, Engineering, and Medicine to generate a percentage contribution of that component to total system cost [80]. Since the study is focused on eventual DAC costs and not FOAK costs, these percentages are then applied to the initial costs defined in Section 3.2.1 for each method. Examples of costs that are not explicitly included in the technical system decomposition that are incorporated in the total initial cost estimates include land-purchase or leasing costs, insurance, G&A, and profit margins. The subsystem learning and improvement rates are chosen based on each component's novelty, scalability, and similarity to other technologies.

The generated emissions costs strongly depend on the type of energy used for electricity and thermal energy, as more carbon-intensive sources will result in more costs to recover the emitted carbon. This provides an estimate of *net CO_2 removed* rather than just absolute CO_2 captured. This results in a more realistic cost estimate for using DAC as a carbon removal technique, rather than just a carbon-neutral one.

S-DAC Decomposition

In the *Negative Emissions Technologies and Reliable Sequestration* report, five scenarios are considered, ranging from best to worst outcomes for S-DAC costs. Within the study, the authors specifically mention that both the "1-Best" and "5-Worst" scenarios are not expected to be reached. Therefore, the S-DAC decomposition costs for this analysis are based on the "2-Low", "3-Mid", and "4-High" scenarios that are cited as more realistic outcomes. The resulting percentage contributions to the total cost of the system are shown in Figure 3.2. The "Generated CO_2 Capture" box represents the additional costs for capturing the CO_2 that is generated by running the system. The assumed energy source is solar for both electricity and thermal energy, so these generated CO_2 capture costs are relatively low compared to other components. [80]

L-DAC Decomposition

The L-DAC information presented in the *Negative Emissions Technologies and Reliable Sequestration* report provides a range of costs due to the maturity of the technologies in the conceptual process analyzed by the committee, rather than the multi-scenario analysis done for S-DAC. For this thesis, an average of the high and low costs for this range has been used to create a representative mid-case for L-DAC. The resulting percentage contributions to total cost of the system are shown in Figure 3.3. [80]

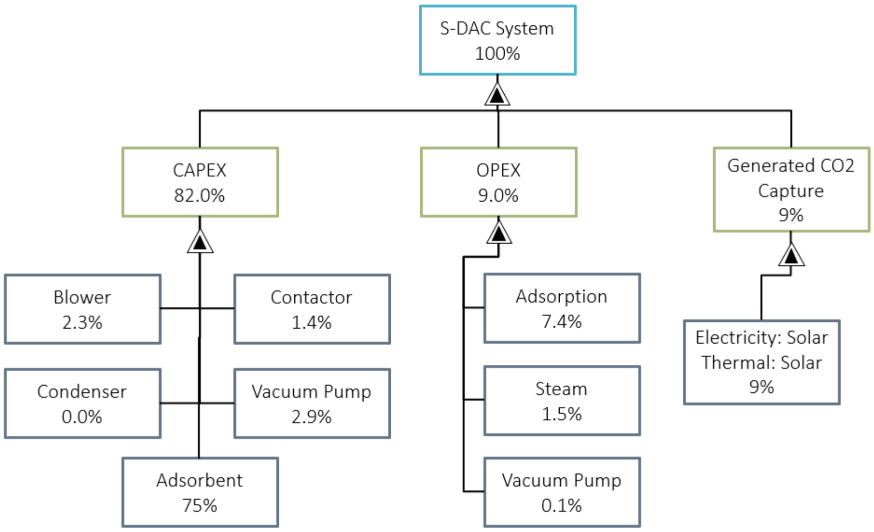

Figure 3.2: S-DAC System decomposition of by cost based on *Negative Emissions Technologies and Reliable Sequestration* 3-Mid Cost Scenario

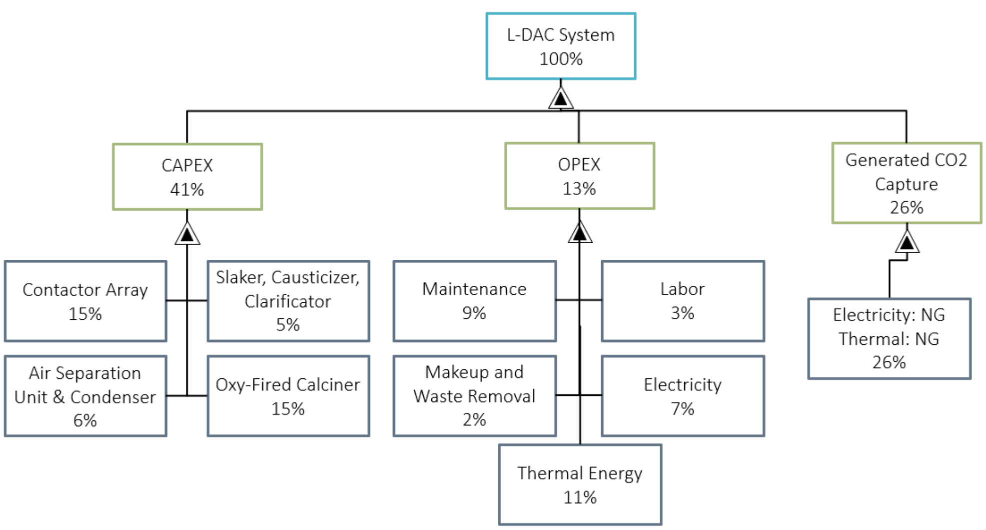

Figure 3.3: L-DAC System decomposition by cost based on average of low and high cost ranges from *Negative Emissions Technologies and Reliable Sequestration* analysis

Analog	Learning Rate	Source	Improvement Rate	Source
Solar PV	23%	[89]	9%	[5]
Wind Energy	12%	[89]	2.9%	[5]
Natural Gas Plants	14%	[89]	7%	[95]
Hydropower Plants	1.4%	[89]	not available	
Nuclear Power	-	[89]	not available	

Table 3.2: Analogs included for this analysis alongside their assumed learning and improvement rates

3.2.4 Analogs and Key Drivers for Technological Change

In preparation for the comparison of existing technologies to DAC, an investigation of key drivers for historical cost trends of each analog is needed. This section addresses this need, first by identifying which technologies will be considered for the analysis, then by outlining the major factors that contributed to their rate of change in cost per the literature.

For this analysis, only energy-related analogs are included. Energy technologies involve significant up-front capital investments whose life cycles last for many years, if not decades, with slow payoffs over time [63]. Because of this, innovations can often come at a slower rate and existing energy systems can be more difficult to displace [82]. Given these unique characteristics, the scope of the analog assessment has been limited to energy systems.

Table 3.2 shows each of the analogs considered, along with the assumed learning and improvement rates if chosen as the appropriate analog. Only solar, wind, and natural gas plants were identified as having an analysis completed for improvement rates, so hydropower and nuclear plants will not be available for this portion of the analysis. Learning rates are much more common across the literature, and a summarized mean one-factor learning rate has been pulled for each technology from the Rubin et al. comprehensive study on electricity supply technology learning rates for use in this thesis [89]. It is worth noting that Rubin et al. determined that the mixed results on nuclear plants for having both positive and negative learning rates indicate this technology may not be an applicable use case for learning-by-doing, which is reflected in the table.

The following subsections outline the key drivers for cost improvement over time for each technology based on the available literature. This supports the creation of evaluation criteria for comparison against DAC technologies to determine the appropriate analogs in Section 4.1.

Solar PV

Solar PV technology has demonstrated higher learning rates than any other energy technology [75] [89]. It is therefore held as the gold standard to aim for by many with regard to future energy technologies. Because of this, there is a significant amount of information regarding solar PV's cost reductions and learning rates in the literature [67] [76] [82].

The most exhaustive investigation of solar PV's cost reductions over time to date can be found in Gregory F. Nemet's book, *How Solar Energy Became Cheap: A Model for Low-Carbon Innovation*. He systematically lays out a comprehensive history of solar PV technology and his findings for the key drivers for its dramatic cost reductions over the last 70 years. He identifies 11 key factors that enabled solar PV to scale as it did, with the goal of creating a model for future energy technologies to build off of to accelerate scaling. The factors are subdivided into three categories: (1) attributes that are specific to the technology itself that enabled scaling, (2) aspects of the production process, and (3) characteristics of the global adoption process. This is summarized in Table 3.3. In addition to these solar-specific characteristics, two additional factors are included in the table under the category of "external support" as they are actions driven by stakeholders external to solar PV providers that enabled cost reductions. While he does not explicitly list them in the solar PV characteristics lists, he does identify them as essential enablers to its scale-up. [82]

Others have studied various aspects of the improvement of solar, but this remains the most holistic analysis. It is therefore the primary source for this technology's analog framework. To ensure consistency with the remainder of the literature, other supporting sources that reference each factor have been added to the table.

Some of the factors listed are less intuitive to understand without additional context than others. "Strong link to scientific phenomenon" is one of these. Nemet points out that solar PV is closely tied to fundamental science, like the structure of atoms and how light works. He further asserts that this strong tie to these principles closely links the development of this technology to academia and government labs, such that government-level R&D spending was particularly effective at building step-by-step improvements. Furthermore, since the theory behind the technology was accessible to all through scientific articles, the fundamental information was able to spread quickly and globally. [82]

Another factor that could benefit from additional information is "openness to technology spillovers". This could apply to many products, but it was particularly important to solar PV due to its modular design. This allowed for stepwise adjustments over time as other domains like the computer industry had breakthroughs that could be applied to solar PV design and manufacturing. It also was able to utilize learnings from wind energy commercialization, particularly in policy structuring and incorporation into the existing power grid. [82]

The last couple of factors to highlight are "automated production suitability" and "tolerance for design compromise". For production automation, the modular make-up of solar PV was key. Many production facilities only produced one level of the value chain, such as just the full modules from receiving the cells from another facility or just the cells after receiving wafers from somewhere else. "Tolerance for design compromise" refers to the Chinese production of solar PV. They took designs that had been good enough to allow for the niche application of solar PV in space and made compromises in efficiency and reliability that allowed them to decrease production costs significantly compared to other countries while meeting the needs for application for power on Earth. [82]

Factor	Category	Impact	Source
Strong link to scientific phenomenon	Device	Enhanced the value of research and design expenditures leading up to and throughout commercialization	[82] [34] [60] [100]
Early convergence on dominant design	Device	Led to focused optimization on that design; others emerged over time and built on learnings	[82]
Development into a standardized product	Device	Enabled efficient installation, labor training, and integration into existing energy systems	[82] [99]
Openness to technology spillovers	Device	Allowed for integration of improvements in other fields, like the computer industry and wind industry	[82]
Massive units of manufacturing production	Production	Enabled constant opportunities for improvement with each production iteration	[82]
Automated production suitability	Production	Shifted innovation focus from the technology itself to improvements within the production process	[82] [12] [60]
Tolerance for design compromise	Production	Willingness to sacrifice small amounts of efficiency enabled large gains in cost reductions	[82]
Relatively low entry cost to production market	Production	Enabled strong competition in production of panels	[82] [34]
Flexibility of modular design	Adoption	Created large number of niche applications to help bridge adoption to grid integration	[82]
Generally appealing to the public	Adoption	Conversations amongst networks of people led to clusters of adoption and local community political support	[82]
Geographically mobile components	Adoption	Ease of shipping of panels and their key components allowed for efficient trade and dispersed supply chains	[82]
Niche markets independent of policy	External Support	High willingness to pay from niche users helped carry solar through policy-support lulls	[82] [100]
Public policy support	External Support	Government support at municipal, state, and national levels at various times globally carried demand	[82] [34] [60] [100]

Table 3.3: Summarized table of solar PV characteristics that enabled scale-up, as described by Nemet (2019)

Wind

While no reference specifically dedicated to analyzing the drivers for wind energy cost reductions over time was found, there was an abundance of literature available discussing learning rates in wind energy technology and several focused on *why* the costs had come down over time. These are significant for developing the evaluation criteria for the use of wind energy as an analog for DAC.

There are many approaches across the literature for wind learning rate analyses. Some focus on wind turbine learning specifically [22], while others focus more generally on the cost of wind energy costs at a larger scale [39] [57]. Many that choose this method subdivide wind energy costs into two categories: onshore and offshore [58] [89]. Onshore wind energy costs will be the main focus of this study since these systems are more similar to the current deployment efforts for DAC. At some point in the future, offshore wind may become a stronger analog if DAC systems begin to move offshore. Wind turbine studies are included in the review since they can help understand drivers of cost reductions at the system level.

Following the example of solar PV, Table 3.4 has been created to summarize key drivers for cost reduction in wind energy found in the literature. The same categories are used for consistency across technologies. There may be factors from solar that could also be argued for wind, but only those specifically found as cost drivers in the literature are included.

Factor	Category	Impact	Source
Improved technology	Device	Makes them cheaper and more productive	[39] [57] [22]
Increase in size	Device	Larger turbines mean increased capacity per turbine, meaning total infrastructure cost decreases	[39] [57] [22]
High capital-to-opex ratio	Device	Capital costs account for 75-90% of wind energy costs, meaning reductions in the production of units has a large impact on the $/kW costs	[39]
Reduction in cost of technology financing	Adoption	Cost of financing decreased as confidence built in the technology	[39]
Manufacturing scale	Production	Economies of scale in manufacturing and supply chains reduce the cost of each wind turbine	[22] [58]
Public policy support	External support	A variety of policies that supported development of the wind industry was highly impactful to cost reductions	[22] [71]

Table 3.4: Summarized table of wind characteristics that enabled cost reductions

Natural Gas Power Plants

Natural gas combined cycle (NGCC) plants, also known as gas turbine combined cycle (GTCC) or combined cycle gas turbine (CCGT) plants, largely began being used for baseload power generation in the 1990s and 2000s. Some NGCCs were built and operated prior to that point, but various ecosystem factors prevented the technology from becoming successful until that time period, and increasing costs were observed. From the 1990s on, a decreasing cost trend for NGCCs is apparent. [20]

Several studies have been done on learning rates before, after, and during the 1990s where a clear change in trend is observed. Depending on the time period chosen, very different results for learning are calculated [89]. The majority of studies on learning for NGCCs in the literature focus on single-factor LRs [20] [75].

Like wind energy, energy costs for natural gas power can be calculated in multiple ways. One can focus solely on the cost of the natural gas turbine or the cost at a plant level to generate electricity from natural gas based on \$/kW or \$/kWh. Rubin et al. show that the average learning rates across the literature for natural gas turbines or energy produced from natural gas plants are very similar [89]. With that in mind, this study focuses on \$/kW generated by NGCC plants as the metric of interest to keep consistent across technologies.

There was limited information in the literature focused on *why* the NGCC plant cost trends occurred, but some papers briefly discuss it. Table 3.5 summarizes the key factors noted from these studies regarding NGCC plant cost trends. While this technology did not undergo rapid cost reductions like solar and wind, the factors outlined in the table illustrate the underlying influences on its rate of cost change. These factors offer insights into potential parallels in cost behaviors for technologies sharing similar characteristics.

The time period covered by the average learning rate being used for this study (1980-1998) includes both the era of negative and positive learning rates. This is a deliberate choice to not bias the study toward overly optimistic outcomes if this is shown to be the right technology to use as an analog for DAC. It is suggested by Kouvaritakis that actions indicative of an oligopoly may be the cause of the negative learning rates within this time period [65].

Hydropower Plants

Hydropower is currently and has historically been the largest contributor to renewable energy production globally [42]. Despite this, there is very limited study on learning rates for hydropower across the literature [92]. It is possible that this is due to its extensive history, with the first industrial use of hydropower in 1880 [69].

The most cited paper for hydropower learning rates comes from Kouvaritakis et al. They report a single-factor learning rate of 1.4% for both small and conventional large hydropower plants from the period of 1975-1993 [65]. This is then cited by many other papers that include hydropower in their learning rate assessments [75] [89]. The original paper and those that reference it do not specify drivers for the reduction in costs for the technology nor the time period covered for the rate estimation, just the rate itself.

Another calculation of a learning rate for hydropower comes from Jamasb. He calculates two-factor learning rates for various electricity generation technologies. For hydropower,

Factor	Category	Impact	Source
Complex systems with individualized project costs	Device	Plants are generally designed and produced on an individual basis, leading to flexibility in size but difficulty in standardizing early on	[20]
Derived from a combination of mature technologies	Device	Technology was created from combining steam turbine and industrial gas turbines, rather than new scientific development	[20] [9]
Relatively low capital with similar OPEX cost compared to other energy sources	Device	Compared to other energy sources at the time (coal, oil, nuclear), NGCCs had relatively low capital costs and short construction time, increasing competitiveness	[20] [9]
Eventual standardization of components for plants	Production	Standardization at a module level allowed for cost reductions in unit price by making production easily repeatable	[20]

Table 3.5: Summarized table of natural gas characteristics that drove cost trends through study timeframe

Factor	Category	Impact	Source
Long plant lifetime	Device	Plants average 80 years or more of use once built	[41] [69]
Site-limited technology	Device	Installation is limited based on where water resources are available	[107]
Large variety of plants sizes in use	Device/ Production	Installations cover a large range of capacity based on the available water and head, from less than 1kW to 22.5GW; limits standardization	[69] [107]
Mature technology	Adoption	Has been used industrially since 1880 with no studies found focused on early adoption	[41] [69] [86]
Government ownership	Adoption	Over the time period studied for LR, the majority of facilities were planned, developed, and operated by governments	[86]

Table 3.6: Hydropower characteristics that are assumed to explain its learning rates

learning-by-doing rates of 1.96% and 0.48% are calculated for large and small hydropower technologies, respectively. The time period of investigation for each of these is 1980-1998 for large and 1988-2001 for small hydropower. For large hydropower, this indicates that the learning rates reported only review a very mature time period, which is supported by the "mature" classification it is assigned. Since these are two-factor estimates, these learning rates are not seen across the rest of the literature focused on one-factor learning rates. [55]

The final calculation of a hydropower learning rate comes from Yao et al. [107]. Their study used a multi-factor approach and calculated a learning rate of 12.25% over the period of 2010-2018. They also attempted to calculate a one-factor learning rate for each technology studied, but note that the one-factor model failed for hydropower due to cost increases over the time period studied.

Given this lack of more detailed information on cost change drivers, the criteria listed in Table 3.6 will be used for the comparison to DAC, based on the examples of solar, wind, and natural gas.

Nuclear Plants

Nuclear plants are unique compared to the other energy technologies included as potential analogs for this study in that they show increasing price trends with cumulative installation several times over their history [35] [89]. This would indicate a negative learning rate over these time periods. While this is certainly not what a new energy technology would want to emulate, it is important to include it in the study to check for similarities between the technologies. If found, this could serve as an early warning sign of possible cost increases over time, rather than the desired learning-by-doing that is anticipated by the industry.

Grubler suggests that using learning rates is not applicable in the case of nuclear power in his investigation of the costs of the French nuclear power scale-up. Despite this being considered the most successful experience with nuclear power, the increasing costs over time still show a negative learning rate. Due to the technology itself, he notes increasing system complexity over time as countries gained more experience constructing, operating, and reacting to problems with the plants. It is worth noting that this study specifically focuses on France with some comparisons to the U.S. over the period of 1970 to 2000. [35]

In a more recent study, Lovering et al. take a broader view of the nuclear cost history by investigating trends through 2015 across seven countries that account for 58% of global reactors. They find that nuclear technology does not have a specific inherent cost trend and caution against using learning rates to predict future costs without incorporating the large variance in trends across countries and time. [72]

For the purposes of this study, the criteria listed in Table 3.7 will be used to determine if nuclear is the most appropriate analog for DAC. If deemed most appropriate, this would indicate that DAC may not be an appropriate technology to use learning or improvement rate analysis for.

Factor	Category	Impact	Source
Construction and operation complexity	Device	The large-scale and inherent complexity of the facilities limit incremental small learnings through experience	[35]
Lack of standardization in reactor design	Production	No historical standardized design for reactors until South Korea in 1989, which showed a positive learning rate through 2008	[72]
Increasing environmental and safety regulations	Adoption	Increased safety standards and system complexity as experience accumulates and incidents occur	[35] [72]

Table 3.7: Summarized table of nuclear power plant characteristics that contributed to negative learning rates

Chapter 4

Results

4.1 DAC Analog Analysis

Using the tables created in Section 3.2.4, each potential analog's key drivers are compared against the four direct air capture methods using the following criteria. Each is based on the author's judgment from what has been read across the literature for each DAC method:

- F: Focus - Alignment with this factor is a focus for this DAC method. It is mentioned regularly by academic articles and company websites in this domain.
- O: Opportunity - There is an opportunity for this DAC method to align with this factor based on the characteristics of the method. It is not something regularly mentioned by those in the domain at this time, but given the features of the method, a path to aligning with this factor is reasonably feasible.
- LO: Limited opportunity - There is limited or no opportunity for this DAC method to align with this factor based on its characteristics.

Table 4.1 summarizes these comparison results. The factors are adjusted from what was shown in the tables in Section 3.2.4 to have more consistency across analogs. An appropriate analog is chosen for each method based on its current and future potential alignment with each factor. Each method's column of results is bolded in the area of the table associated with this chosen analog. **S-DAC, ESA-DAC, and m-DAC align best with solar**, while **L-DAC pairs best with natural gas power plants** based on the criteria evaluated. Based on these results, solar is used as the analog for S-DAC, and natural gas plants are used as the analog for L-DAC for all single-factor LR and IR analyses.

There may be some factors that are listed for one technology in the table that would actually be applicable to another. For example, wind energy also has niche markets that likely supported its cost declines, but it was not cited in the literature as being a driver for cost reductions. The table only includes what could be found for each technology specifically with regard to driving cost reduction.

Figure 4.1 shows the single-factor learning rate for all of the analogs investigated for both L-DAC and S-DAC for reference to demonstrate the full range of these energy technology learning curves on each method. The curve associated with the chosen analog for each DAC method is boxed in yellow within the legend.

Table 4.1: Summary of full analog analysis for DAC

	Factor	Category	S-DAC	L-DAC	ESA-DAC	m-DAC
Solar	Strong link to scientific phenomenon	Device	**O**	O	**O**	**O**
	Early convergence on dominant design	Device	**O**	O	**O**	**O**
	Development into a standardized product	Device	**O**	LO	**O**	**O**
	Openness to technology spillovers	Device	**F**	O	**F**	**F**
	Massive units of production	Production	**F**	LO	**F**	**F**
	Automated production suitability	Production	**O**	LO	**O**	**O**
	Tolerance for design compromise	Production	**O**	O	**O**	**O**
	Relatively low entry cost to production market	Production	**O**	O	**O**	**O**
	Flexibility of a modular design	Adoption	**F**	LO	**F**	**F**
	Appealing to the public	Adoption	**F**	O	**F**	**F**
	Geographically mobile components	Adoption	**F**	LO	**F**	**F**
	Niche markets independent of policy	External Support	**F**	F	**F**	**F**
	Public policy support	External Support	**F**	F	**F**	**F**
Wind	Improved technology	Device	O	O	O	O
	Increase in size for economies of scale	Device	O	F	O	LO
	High capital-to-opex ratio	Device	LO	LO	LO	LO
	Reduction in cost of technology financing	Adoption	O	O	O	O
	Large units of production	Production	F	LO	F	F
	Public policy support	External Support	F	F	F	F

Continued on next page

Table 4.1: Summary of full analog analysis for DAC (Continued)

Natural Gas Plants	Complex systems with individualized project cost	Device	LO	**O**	LO	LO
	Standardization of components for plants	Device	F	**O**	F	F
	Derived from a combination of mature technologies	Device	LO	**F**	LO	O
	Relatively low capital cost compared to other options	Device	O	**F**	O	O
Hydropower	Long plant lifetime	Device	LO	LO	LO	LO
	Site limited technology	Device	LO	LO	LO	LO
	Large variety of plant sizes in use (not unit scalable)	Device/ Production	LO	O	LO	LO
	Mature technology	Adoption	LO	LO	LO	LO
	Government ownership	Adoption	LO	LO	LO	LO
Nuclear	Construction and operation complexity	Device	LO	LO	LO	LO
	Increasing environmental and safety regulations	Adoption	O	O	O	O
	Lack of standardization in reactors	Production	LO	O	LO	LO

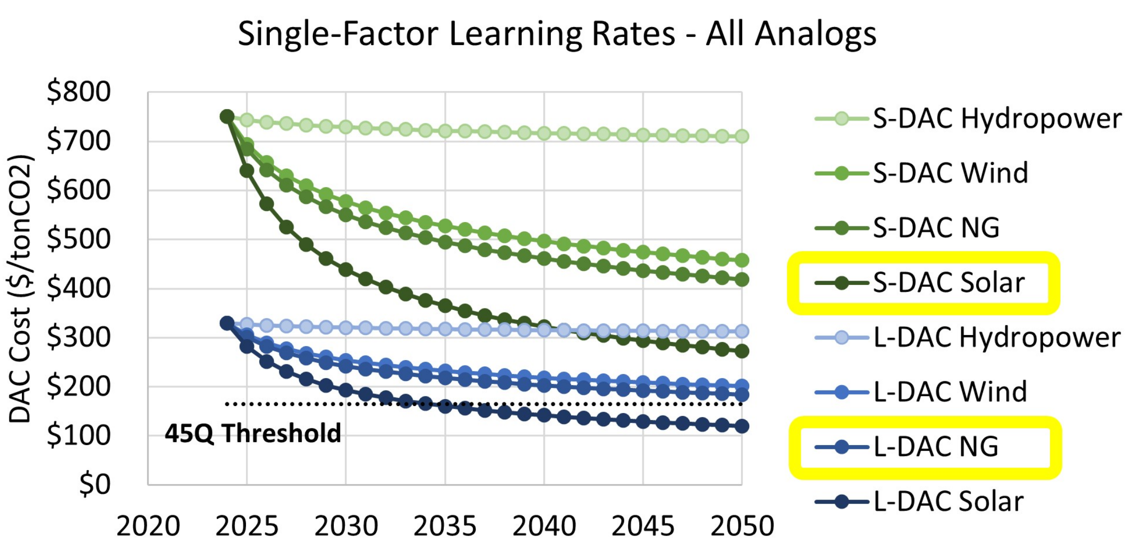

Figure 4.1: Comparison of cost reduction estimates using single-factor learning rates across all analogs considered for S-DAC and L-DAC (excluding nuclear)

4.2 DAC Cost Reduction Rate Analysis

All plots in this section follow consistent formatting as follows:

- **Green coloring** - Indicates S-DAC cost curve
- **Blue coloring** - Indicates L-DAC cost curve
- **Circle markers** - Indicates learning rate utilized for analysis
- **Triangle markers** - Indicates improvement rate utilized for analysis
- **Solid markers** - Indicates single-factor analysis
- **Empty markers** - Indicates component-based analysis
- **45Q Threshold** - Indicates the \$165/tonCO_2 threshold at which the cost of DAC reaches the U.S. government tax credit for DACCS (assuming cost of compression, transport, and storage is on average \$15/tonCO_2 [80])

4.2.1 Single-Factor Analysis Results

Figure 4.2 shows the projected DAC costs for S-DAC and L-DAC relative to each other and to the 45Q reference point using single-factor learning and improvement rates. The learning and improvement rate curves follow similar trends for both approaches until around 2030 when they start to diverge. Only the improvement rate curves reach the 45Q threshold by 2050 for each DAC method. L-DAC reaches the threshold in 2034, while S-DAC reaches it six years later. The learning rate curves are much shallower after the 2030 diversion point, with S-DAC hovering around \$300/tonCO_2 beyond 2040 and L-DAC flattening to about \$200/tonCO_2.

4.2.2 Component-Based Analysis Results

The results from the component learning and improvement rate analyses can be seen in Figure 4.3. Figures 4.4 and 4.5 show the cost breakdown across the years of study at a component level for the learning rate curves as reference for how these curves were built. For the full breakdown of the component-level analysis and how these curves were created, see Appendix A.

Much like the single-factor analysis, the improvement and learning rate curves follow similar trends for a few years before diverging. However, the point of divergence is 3-4 years earlier than with the single-factor rate estimates. Again, only the improvement rate curves reach the 45Q threshold. Here, L-DAC reaches the threshold about a year later than predicted using single-factor rates, while S-DAC reaches it at about the same time. The declines for the learning rate curves using component analysis are overall more shallow than the single-factor, particularly for L-DAC.

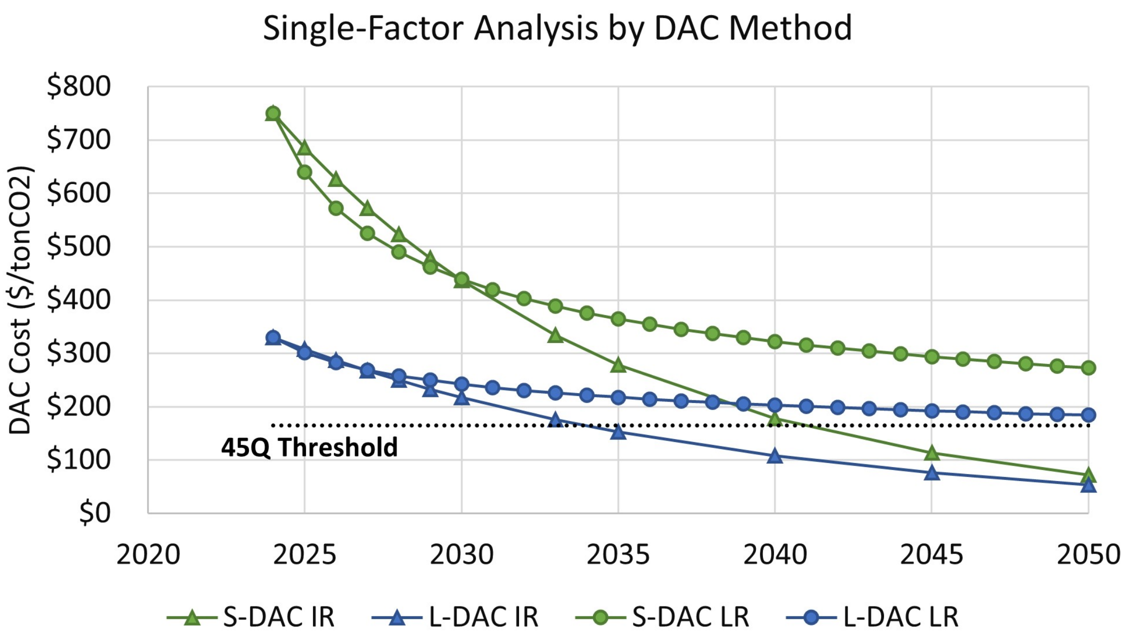

Figure 4.2: Comparison of cost reduction estimates using single-factor learning rates versus improvement rates for S-DAC and L-DAC

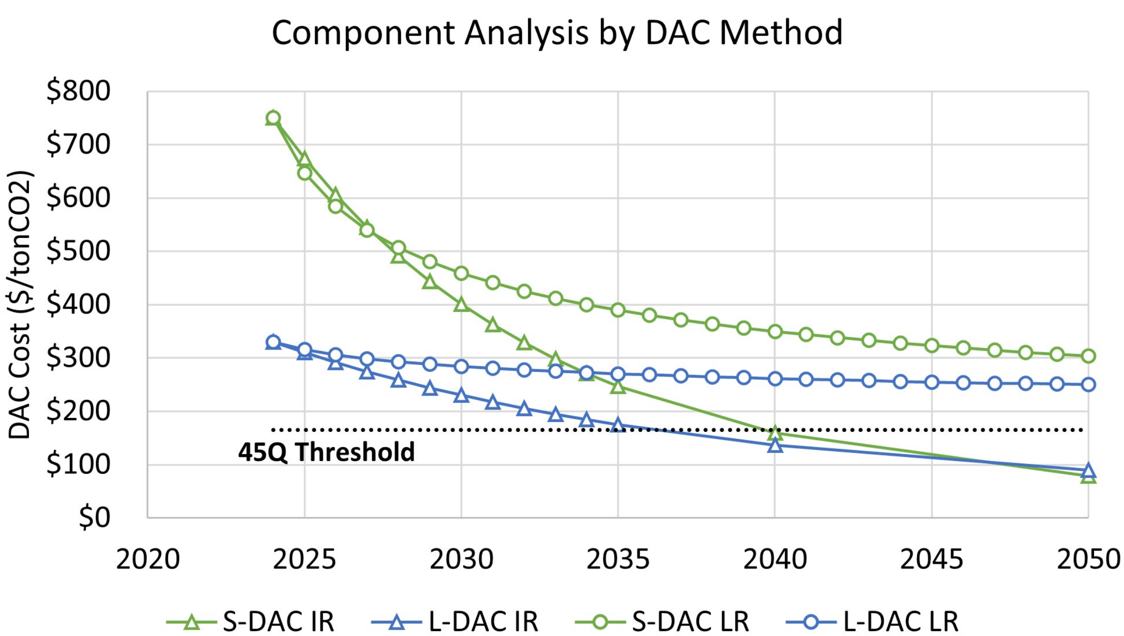

Figure 4.3: Comparison of cost reduction estimates using component learning rates versus improvement rates for S-DAC and L-DAC

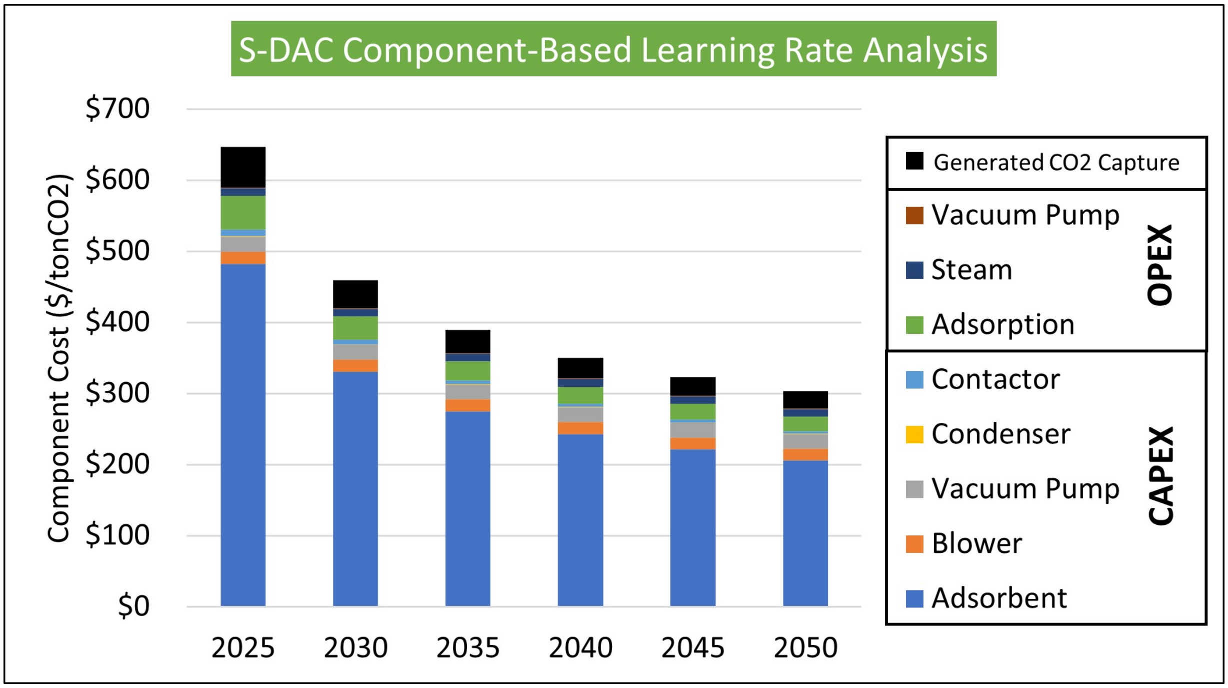

Figure 4.4: Cost breakdown by components for S-DAC learning rate component analysis

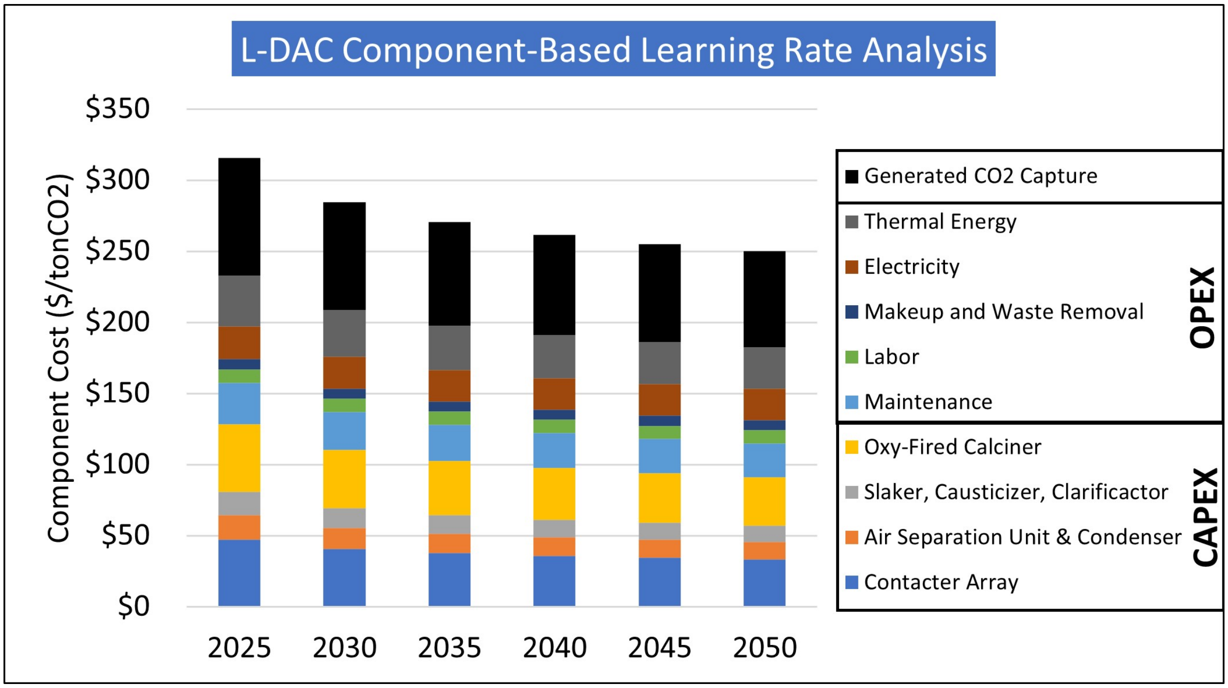

Figure 4.5: Cost breakdown by components for L-DAC learning rate component analysis

4.2.3 Base Results Comparison by DAC Method

This section shows the same information as Sections 4.2.1 and 4.2.2, just in an alternate view that enables a better comparison of cost reduction forecasts using base case assumptions by DAC method. Figure 4.6 shows the results for S-DAC, and Figure 4.7 shows the same for L-DAC. Table 4.2 shows the year each curve crosses \$200/tonCO_2 and the 45Q threshold for all curves investigated in the base case.

Viewing the information in this way emphasizes the alignment of all estimation approaches for the first several years. It also emphasizes that in most cases, the single-factor approach is more optimistic than the component-based approach. The exception to this is the improvement rate analyses for S-DAC. Here, the component analysis shows a faster decline than the single-factor approach. This difference in behavior will be discussed further in Chapter 5.

		S-DAC		L-DAC	
Scenario	Approach	\$200/tCO_2	45Q Threshold	\$200/tCO_2	45Q Threshold
One-Factor	LR	-	-	2041	-
Component	LR	-	-	-	-
One-Factor	IR	2039	2041	2032	2034
Component	IR	2038	2040	2033	2037

Table 4.2: Summary of base cost reduction forecast results, showing when \$200/tCO_2 and 45Q threshold are reached

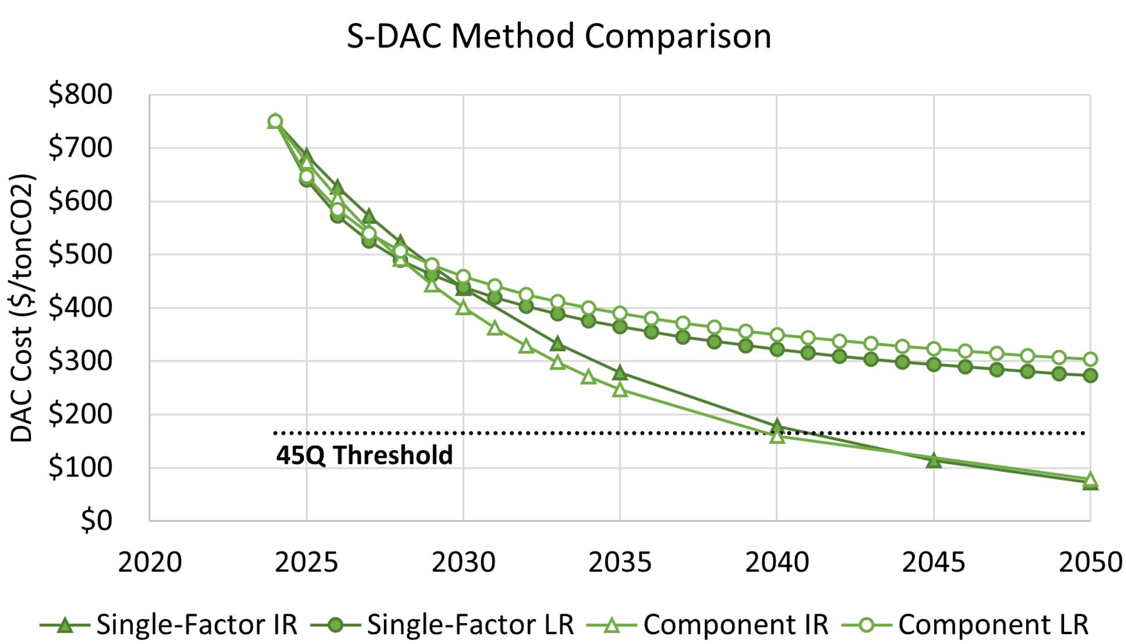

Figure 4.6: Comparison of cost forecasts for S-DAC using base case assumptions across all analysis approaches

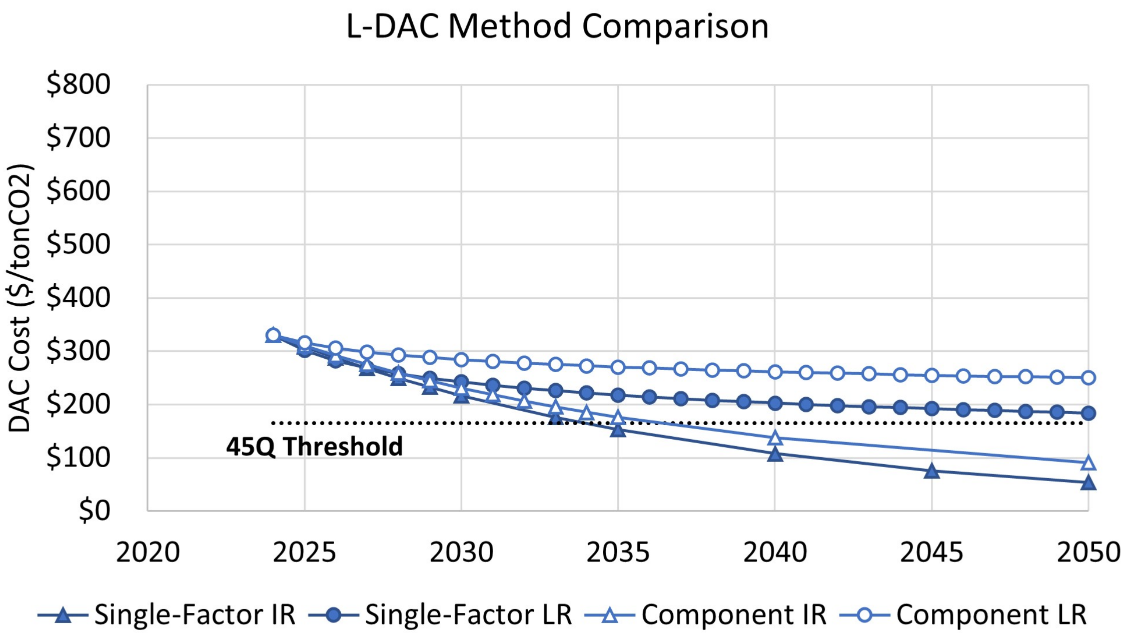

Figure 4.7: Comparison of cost forecasts for L-DAC using base case assumptions across all analysis approaches

4.3 Sensitivities

Two overarching sensitivity sets of cases were investigated. The first uses the alternate DAC scale-up scenarios introduced in Section 3.2.2, showing how these alternate growth rates impact the timing of reaching the 45Q threshold introduced in Section 4.2. The second explores how varying the learning and improvement rate ranges beyond the base assumptions impacts this timing, as there is variability in the literature regarding the most appropriate rate to use for each analog.

4.3.1 Sensitivity to DAC Scale-Up Scenarios

This set of sensitivity cases helps demonstrate the cost curve response to varying the DAC scale-up rate for the experience curve analyses due to the high uncertainty of the scale-up rate. Figure 4.8 shows the results for S-DAC and Figure 4.9 for L-DAC. Both are shown at 5-year increments for readability.

Within these sensitivity cases, Base is the only case that does not reach \$200/tonCO_2 by 2050. Base and the IEA WEO STEPS case are the only cases that don't reach the 45Q threshold by this time. The Solar Scale-Up case shows a very rapid decline compared to the other cases, reaching the 45Q threshold sometime between 2030 and 2035. The remaining cases reach the threshold ranging from 2039 to 2050.

L-DAC shows a similar story but varies in a few key places. First, its Natural Gas Scale-Up case is the most conservative case in the set, ending nowhere near the 45Q threshold by 2050. Other than Base and NG Scale-Up, all sensitivities reach the 45Q threshold by 2050,

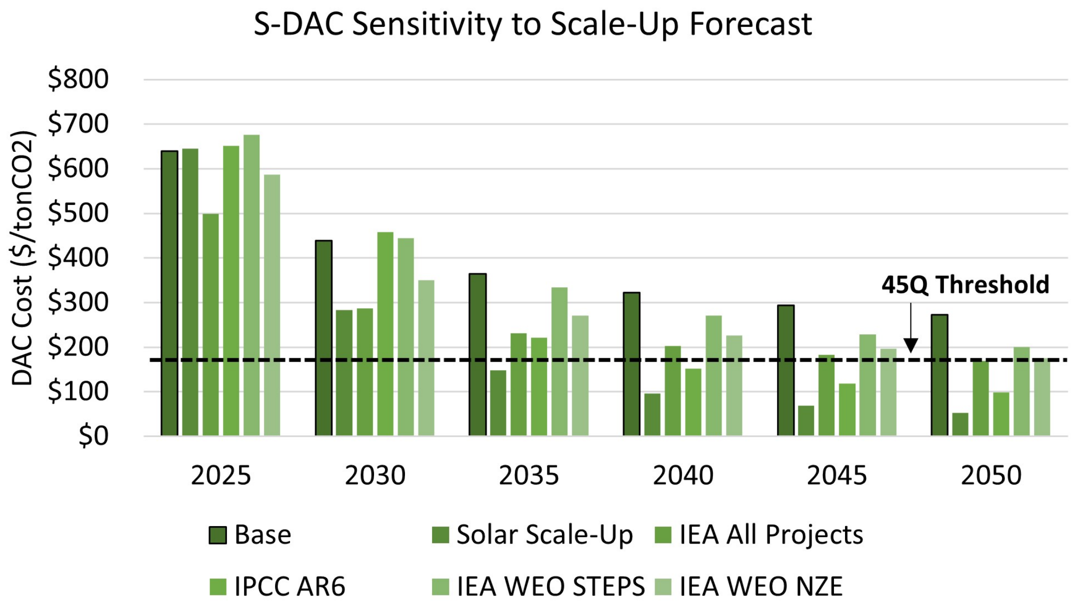

Figure 4.8: Impact of alternate S-DAC experience growth rates on cost forecasts compared to base single-factor learning rate result

with most reaching it by 2040. By 2050, all cases other than NG Scale-Up are in the range of \$100/tonCO_2-\$200/tonCO_2.

4.3.2 Sensitivity to Learning and Improvement Rate Ranges

This sensitivity assessment helps illustrate the variability of outcomes depending on the analog learning and improvement rates used from the literature. Figure 4.10 shows the results for S-DAC and Figure 4.11 for L-DAC. Table 4.3 shows the range of rates used for each analysis.

The range of learning and improvement rates seen in the literature is broad, and therefore the results of this sensitivity assessment are wide. For both DAC methods, improvement rates continue to show much steeper declines than learning rates on both ends of the range. The High IR cases are both well below \$50/tonCO_2 by 2050. Beyond those, only Base IR and the High LR cases dip below the 45Q threshold for S-DAC. For L-DAC, in addition to those cases, the Low IR case also reaches the 45Q threshold by 2050.

Analog	Approach	Average	Range		Source
			Low	High	
Solar	LR	23%	15%	35%	[89]
	IR	9%	4%	14%	[5]
Natural Gas Plant	LR	14%	10%	24%	[89]
	IR	7%	3%	13%	[95]

Table 4.3: Range of learning and improvement rates used for sensitivity analysis

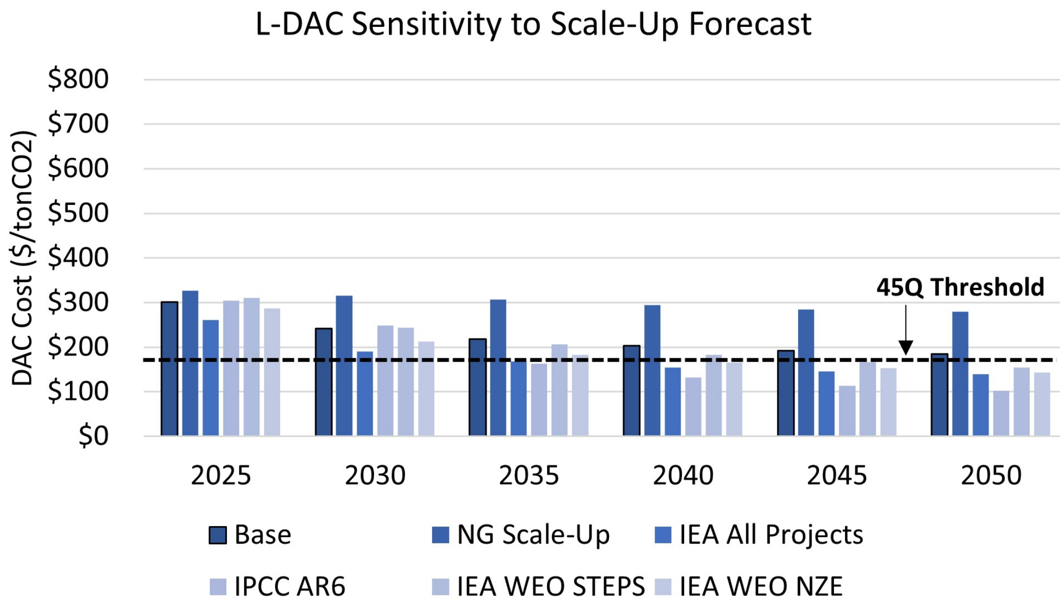

Figure 4.9: Impact of alternate L-DAC experience growth rates on cost forecasts compared to base single-factor learning rate result

4.3.3 Summary

Table 4.5 summarizes the timing for reaching the key thresholds for each method across all scenarios considered. Finally, Figures 4.12 and 4.13 are summary plots that show the range of outcomes for both DAC methods.

S-DAC exhibits a 76% variance to the single-factor base case for the scale-up rate sensitivities. The variance is much higher for the analog rate sensitivities at 132%. Given the unreliability of IR calculations over this length of time, these were removed from the set resulting in a variance of 90% for the analog rate sensitivities. Similarly, the analog scale-up case can be removed from the scale-up sensitivity set as an extreme outlier, resulting in a variance of 35%.

Variance to the base case is generally less high for L-DAC than for S-DAC. Compared directly without removing any cases, the scale-up sensitivity set shows a variance of 89% and the analog rate set shows a variance of 105%. Once corrected for the concerns discussed in the S-DAC section, the scale-up sensitivity set shows a variance of 26% and the analog rate set 53%. This is summarized in Table 4.4.

Overall, both DAC methods are more sensitive to the analog rate used than to the scale-up rate. S-DAC is more sensitive to both scale-up rate and analog rate than L-DAC, which would be expected given its steeper declines.

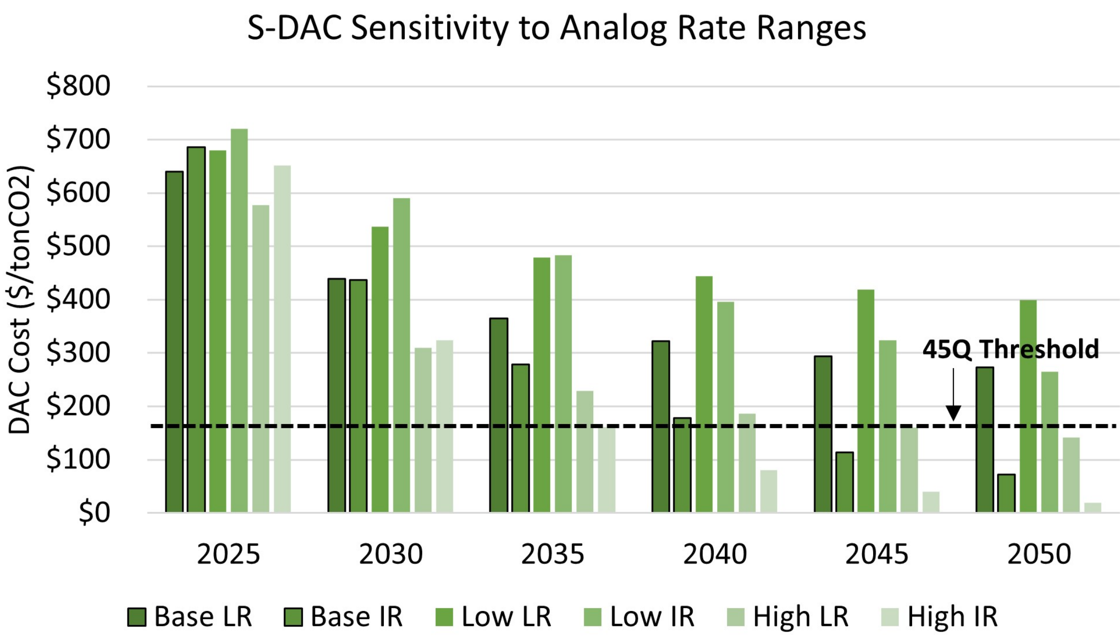

Figure 4.10: Impact of varying S-DAC analog (solar) learning and improvement rates across range from literature

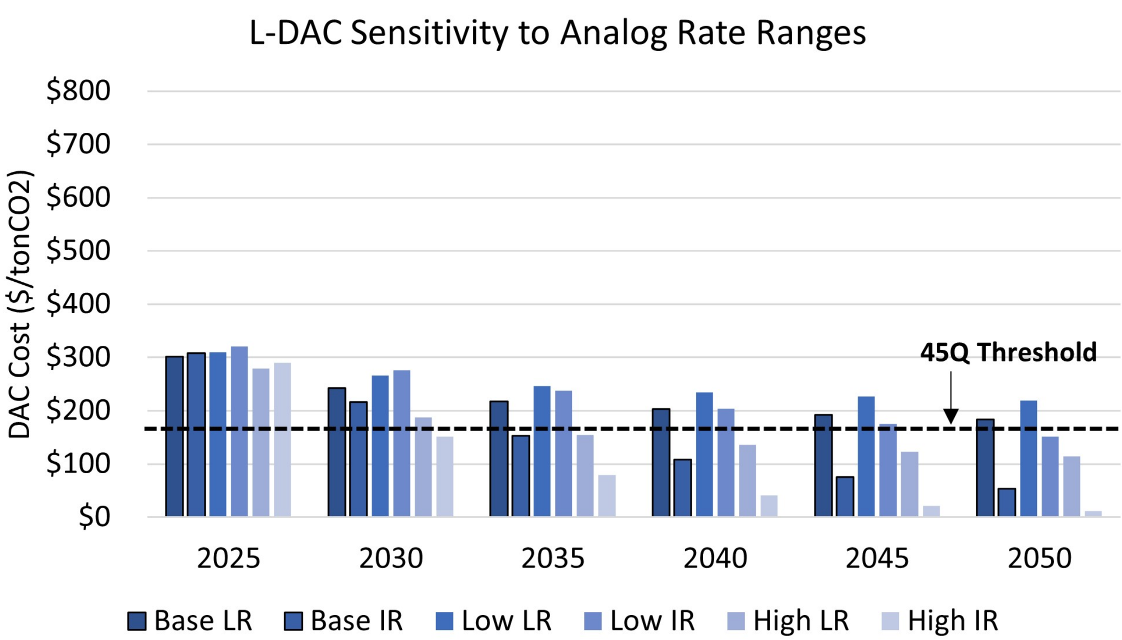

Figure 4.11: Impact of varying L-DAC analog (natural gas plants) learning and improvement rates across range from literature

	S-DAC		L-DAC	
	Scale-up	Analog rate	Scale-up	Analog rate
Sensitivity to baseline	76%	132%	89%	105%
Sensitivity with outliers removed	35%	90%	26%	53%

Table 4.4: Variance of sensitivity sets to single-factor base case

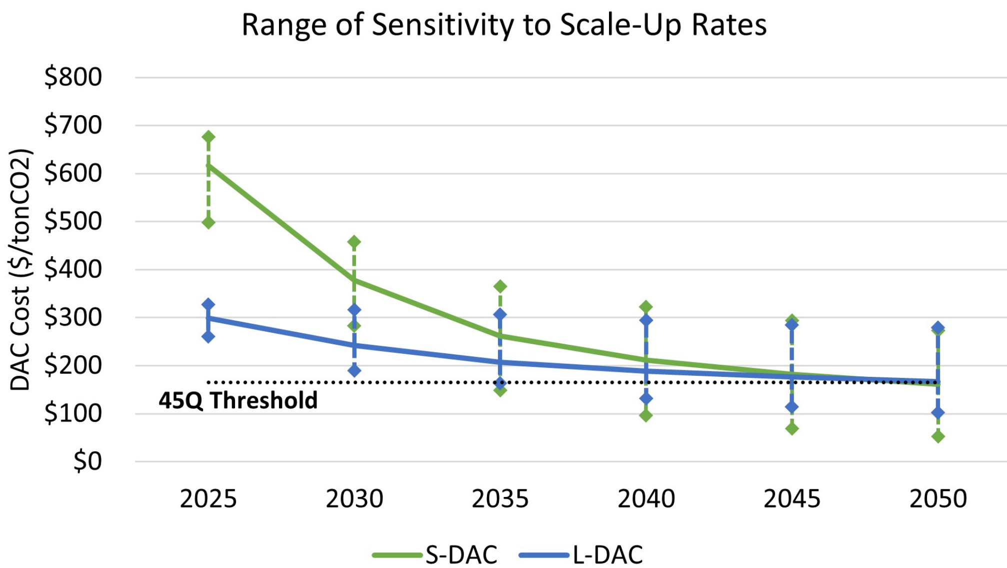

Figure 4.12: Summary plot showing the range of sensitivity to scale-up rate for both DAC methods

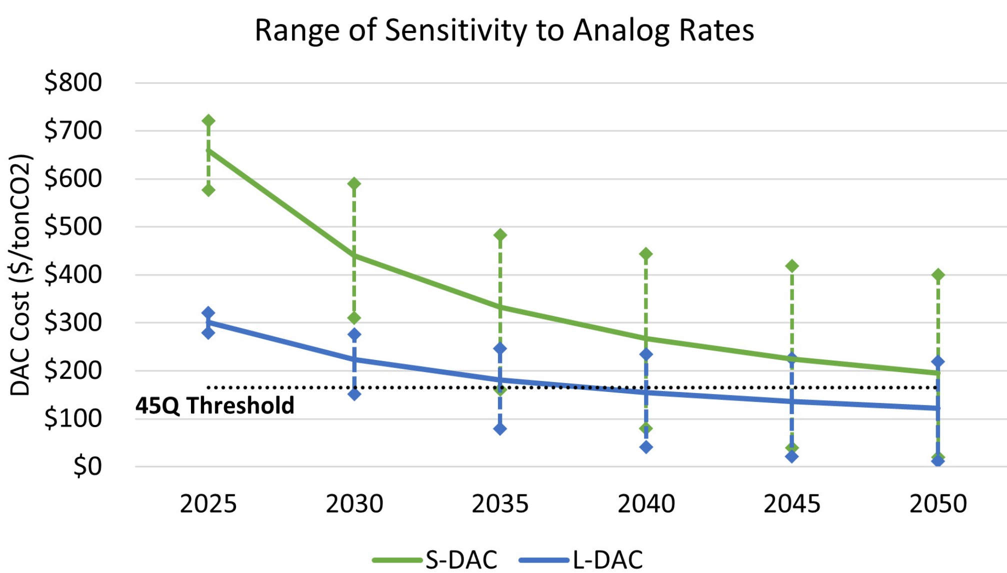

Figure 4.13: Summary plot showing the range of sensitivity to analog rate utilized for both DAC methods

		S-DAC		L-DAC	
Scenario	Approach	\$200/tCO_2	45Q Threshold	\$200/tCO_2	45Q Threshold
Base One-Factor	LR	-	-	2041	-
Base Component	LR	-	-	-	-
Base One-Factor	IR	2039	2041	2032	2034
Base Component	IR	2038	2040	2033	2037
Analog Scale-Up	LR	2032	2034	-	-
IEA All Projects	LR	2041	-	2029	2036
IPCC AR6	LR	2037	2039	2033	2035
IEA WEO STEPS	LR	2050	-	2037	2046
IEA WEO NZE	LR	2045	-	2032	2040
Base Low LR	LR	-	-	-	-
Base Low IR	IR	-	-	2041	2048
Base High LR	LR	2039	2044	2029	2033
Base High iR	IR	2034	2035	2038	2030

Table 4.5: Summary of all cost forecast results, including sensitivities

Chapter 5

Discussion of Results

This chapter discusses the results of the analysis and the key findings in the context of the research questions from Section 1.3:

1. The IPCC estimates needing 2.8 (0.5-11 range) $GtCO_2$/yr of non-conventional carbon removal by 2050, but current removal rates are well below this. If DAC adoption and cost reduction behave similarly to solar PV or other analogous technologies, what contribution can it realistically expect to make to the CO_2 removal portfolio?
   (a) How might scale-up rate and cost reduction vary by DAC method?
   (b) What does the literature identify as the key drivers for analogous technology learning and improvement, and how do those compare to the various DAC methods?
   (c) What role are the public and private sectors currently playing in advancing the DAC market, and how does this compare to analogs?
2. Based on the answers to Question 1, what actions could be taken in the near term regarding DAC by governments, DAC providers, and DAC purchasers to help accelerate the reduction of DAC costs?

5.1 Cost Reduction Analysis

The results in Section 4.2 and 4.3 help shed light on scale-up rate and cost reduction variances across DAC methods from Research Question 1a. As shown in the results, the rate of cost reduction predictions varied drastically across DAC methods. This is expected given the difference in analogs used for the learning and improvement rates. It emphasizes the importance of carefully considering which DAC method is being investigated when using technological change analysis. Ideally, these analyses would focus on either S-DAC or L-DAC (or some other specific method once these reach the commercialization phase), but if an industry-wide analysis is undergone, careful consideration should be given to the appropriate learning or improvement rate to choose.

In Section 4.2, it was noted that using this baseline scale-up rate for the learning curves did not result in reaching the 45Q threshold across DAC methods. This suggests that if projects are not accelerated beyond the rate of scale-up projected by the IEA's Advanced Development scenario, DAC may struggle to reach a price that would be fully offset by current U.S. government tax credits by 2050, regardless of method. This is not inherently surprising, as it was noted when choosing this scale-up estimate as the baseline that it was fairly conservative. However, it does indicate that even if DAC does not scale up as quickly as often forecasted, it may still come down the cost curve far enough to compete with hard-to-abate emission mitigation options by 2050 if the cost of those mitigations is above \$300/tonCO_2.

The sensitivities investigated with alternate scale-up rates shed light on potentially less pessimistic cost reduction forecasts compared to the baseline. Almost all of these sensitivities across DAC methods reach \$200/tonCO_2 by 2050. This makes sense since three out of five of the sensitivities are goal-derived forecasts of what will be needed rather than projections of what projects are actually in the queue. However, the IEA full project queue shows costs at or below the 45Q threshold for both DAC methods by 2050, indicating that if projects proceed as projected, costs may be in range for full tax credit offset in the U.S. by midcentury. It is also worth noting that the IEA WEO STEPS scenario also dips below \$200/tonCO_2 for both methods by this date, so if countries stick to their commitments, the cost could be reasonably competitive with other CDR and mitigation options by 2050.

In Section 4.3.3, it is noted that both DAC methods investigated were more sensitive to the analog rate used than to the scale-up rates. The range of learning rates across the literature for both methods was fairly wide to begin with, so this is not necessarily an unexpected result. It emphasizes the importance of choosing the appropriate analog as a first step for any analysis using learning rates, then the importance of selecting the appropriate learning rate for that analog from the literature. This would be especially important for technologies using a higher learning rate, like S-DAC, since the impacts of this choice are amplified at higher decline rates.

While the DAC methods were more sensitive to the analog rate use, there was also significant sensitivity to the scale-up rates. The base scale-up rate was chosen since it had the highest level of confidence compared to the other options, but given the high level of sensitivity to the scale-up rates, the results of the study would likely look quite different with a different base scale-up rate. If DAC can scale closer to any of the sensitivity rates based on projections or goal-derived, there is a much higher likelihood of reaching the \$200/tonCO_2 and 45Q thresholds before mid-century. It is worth noting that the compounding impact of an alternate scale-up rate alongside an alternate learning rate for the analogs was not considered for this analysis.

Given the high levels of sensitivity for both DAC methods across the sensitivity cases investigated, it is worth considering what additional data might help narrow these ranges. Higher confidence projections will likely become available for scale-up rate once the first commercial L-DAC plant begins operating in 2024. The IEA is tracking announced project capacities expected, but this is a space that perhaps an organization like the DAC Coalition could follow at a more granular level, perhaps by DAC method, to help understand this for future studies. The range of learning rates for each analog across the literature could potentially be narrowed by looking for outliers in the range and understanding if they are appropriate to include or not. Much of this range narrowing would be accomplished by focusing a study directly on this for each analog.

Within the scale-up rate sensitivity cases, the analog scale-up scenarios stand out as clear outliers. The solar scale-up scenario for S-DAC shows a drastic reduction in costs, while the natural gas scale-up scenario for L-DAC shows hardly any cost reduction over the 25-year period. The extreme results from both of these cases call into question their validity for use in the analysis.

In general, the improvement rate analyses result in much lower costs by 2050 compared to the learning rate analyses. As discussed in Section 2.3, these two technological change approaches are equivalent when the scale-up rate for a technology experiences exponential growth. Since that is not the case for the baseline scale-up rate used, it follows that the two approaches would experience different cost reduction rates. Based on the study from Nagy et al. comparing across approaches, the learning rate analyses would provide a higher level of confidence for a 25-year study such as this [79].

Overall, the analysis supports the hypothesis that there is value in considering each method of DAC separately for both choosing the analogs used in the analog analysis and for the cost reduction analysis itself. The large variance reported in the literature for the initial costs of each DAC method further supports considering the two separately. To address the specific research question, scale-up may overall occur at a similar rate for S-DAC and L-DAC, but the cost reduction pathways were found to vary drastically across the two DAC methods.

5.1.1 S-DAC

Despite initial costs that are almost double the initial estimates for L-DAC, the focus on modularity and scalability for S-DAC results in rapid forecasted cost reductions. This rapid decline leads to potentially similar costs between the two DAC methods by 2050, assuming similar scale-up rates.

Because of the high initial costs for S-DAC, this DAC method relies on behaving similarly to solar PV in its technological change process to reach costs that are competitive with L-DAC. If S-DAC is unable to follow the scalability path of solar PV and instead finds itself closer to a different analog, such as its second closest analog, wind energy, it may be difficult to reach competitive cost thresholds. Several of the items listed as opportunities, or "O", in Table 4.1 highlight these risks. If S-DAC is unable to achieve the production economies of scale and automation that were so critical to solar PV cost reductions, it may find itself more similar to wind energy as an analog. This scenario could be caused by a lack of standardization of the product for installation, labor training, and integration purposes or if the domain does not on a dominant design to make it worth creating these large production facilities. If this were to occur, cost reduction forecasts may look more similar to the Low LR Analog Rate sensitivity case since the 15% LR it used is close to the 12% LR of wind energy from the literature.

The range of 2050 cost results for the scale-up sensitivities, excluding the solar scale-up rate, of about \$100-\$300/tonCO_2 is very consistent with the range estimated by Fuss et al. for nth plants costs [31]. This provides confidence in the results of the analysis.

5.1.2 L-DAC

Since it starts at a much lower initial cost than S-DAC, L-DAC is less dependent on learning-by-doing for reaching competitive cost thresholds. The focus of this method is more on economies of scale rather than learning-by-doing, which explains the lower initial cost and slower learning rate. This is very consistent with its analog, the natural gas power plant.

There is a key concern with these results to keep top of mind, however. Since actual commercial costs are not yet available, the average cost across several sources has been used for the analysis, as described in Section 3.2.1. If actual costs end up being much higher than this average, this DAC method may struggle to reach a competitive cost by mid-century. This is a real concern since, as discussed in Section 2.3.1, the pre-learning phase for new technologies often has escalating prices before learning begins.

5.2 Implications of Architectural Decisions on Cost Reduction Behavior

The combination of findings from Section 3.2.4 and the results in Section 4.1 help answer Research Question 1b. Section 3.2.4 provides a direct answer to the question of what are the key drivers for technological change of analogous technologies, while Section 4.1 addresses how those analogs compare to DAC methods. The answers to these questions can help provide insight into the impacts of early architectural decisions across the DAC methods to how each may see cost reductions over time.

The analog analysis from Section 4.1 showed that S-DAC, m-DAC, and ESA-DAC are all on a very different trajectory from an analog perspective compared to L-DAC. While solar had many drivers for its scale-up and cost reduction path identified, the following are three specific to design choices made by the companies developing it. Shown alongside each are the associated factors from Table 3.3 that were enabled by the decision:

- Standardization - Early convergence on dominant design; development into a standardized product; massive units of manufacturing production; automated production suitability

- Modularity - Openness to technology spillovers; flexibility of modular design; geographically mobile components

- Design compromise - Tolerance for design compromise

Standardization and convergence on a common design is an area of opportunity for S-DAC over the next several years. These can enable the massive units of manufacturing production and automation that were so beneficial to solar PV cost reductions. However, S-DAC has a multitude of designs across companies currently, which cannot be manufactured at a large scale. As certain designs emerge as successes within the S-DAC industry, quick convergence on a design may help drive costs down at an industry level. As pilot designs have not yet emerged for m-DAC and ESA-DAC, this is less immediately important for their consideration, but it is something to keep in mind if these methods mature.

Modularity is a design choice that is referenced regularly by S-DAC and ESA-DAC and has been mentioned for m-DAC. This is the characteristic most associated with quick learning for this technology. The openness to knowledge spillovers from other technologies and flexibility of modular design for learning with each iteration is of particular focus. Companies also seem to have a focus on keeping components easy to ship for global mobility, like Climeworks' design to have six of their modular units fit into one shipping container [84].

Tolerance for design compromise was one opportunity that was not seen in the literature and across company websites for S-DAC providers. Depending on the needs of the storage method used by the provider, there may be an opportunity to adjust designs for the S-DAC system in the future to allow for this if it helps reduce costs. This may also be something to consider in the development of either of the two less mature methods.

The factors driving natural gas plant cost trends in the literature can also provide insights for L-DAC plant design, showing where providers could alter the early design and project planning to potentially see higher learning and improvement rates than seen by natural gas plants. The companies pursuing this method are focused on economies of scale for CO_2 removal by building large continuously running DAC plants. However, the standardization of components within the plants and standardization of the design of the plants could help see the manufacturing economy of scale that was noted as a key driver for solar PV cost reductions for components within the plants. A focus on systems engineering in the plant design stage could also help avoid unnecessary complexities with such a large system.

The factors across the technologies studied for the analog analysis are a combination of direct drivers that could be explicitly modeled and qualitative arguments that would be difficult to prove with a model, particularly in the case of solar PV. This makes comparing how well-aligned the DAC methods align with their analog on particular factors difficult. For example, time to converge on a dominant design is something that could be put into a model and compared across technologies, but "openness to technology spillovers" would be difficult to assign an actual metric to. Because of this, the analog analysis itself is quite qualitative and based on consistent themes for technologies more than numerical evaluation. A study focused on a more numerical evaluation could be pursued by assigning metrics to each factor to try and estimate how each compares across technologies, but it may be unable to incorporate some of these more qualitative factors that were impactful to a technology like solar PV.

Many of the factors within the table are assumed to be independent since they are listed as independent factors but are, in fact, potentially quite intertwined. For example, early convergence on a dominant design in solar PV made developing standards across products much simpler. It also helped drastically with massive units of production, which made it worth the time it would take to invest in automating that same production. Policy support in the U.S. through R&D and public procurement carried solar production for several years until policies changed, at which point the niche market in Japan picked up the development of the product until policy in Germany drove huge manufacturing growth. It is the connected system of all of these factors that enabled the technology to scale as it did, rather than each item independently. [82]

This interconnectedness of factors is especially true with solar PV but is also true for the other analogs considered. For example, an increase in the size of windmills to allow for economies of scale drives capital-to-opex ratios higher than they would otherwise be.

Because hydropower is site limited based on existing bodies of water, it drives plant sizes to vary significantly in size to match the resource at each site. It is important for DAC providers to keep these interconnections in mind when developing the product rather than just focusing on one or two factors to try and mimic.

One key takeaway from the analog study is the misalignment of L-DAC with solar as an analog at a high level. While it could take learnings from solar PV's cost reduction path to improve beyond natural gas learning rates, it is not a suitable overall analog. The DAC industry as a whole did not have a common analog applicable to all methods due to the very different paths the two mature methods are intentionally pursuing. The less mature methods still have time for architectural decision changes as they approach pilot and commercial phases of development if they see that one pathway is more successful or more aligned with their goals.

5.3 Public and Private Sector Influence

While the estimations of cost reductions for DAC are important for understanding the future of the technology, it is also important to consider how these scale-up and cost reduction predictions interact with the larger DAC market ecosystem. The current involvement of the public and private sectors in the DAC market is introduced in Section 2.2.4. This section will provide extra discussion relevant to the results that together work to answer Research Question 1c.

Over the last three years, governments across the world have become more active in carbon removal support and direct air capture, as described in Section 2.2.4. Policies that mimic some that were particularly influential for solar have started to emerge. Nemet identifies early-stage procurement in the U.S. from the U.S. Block Buy program in the 1970s and 1980s as one of the key catalysts in developing the manufacturing and production processes that were instrumental to solar PV's scale-up and cost reductions [82]. While no direct procurement policies are currently in place for DAC, many of the competition and prizes for funding in place in the U.S. today could have similar effects on DAC, particularly the DAC hub program.

The private sector is also playing a particularly active role in the DAC ecosystem despite the very high costs associated with carbon removal using DAC available today. As discussed in Section 2.2.4, there is a significant amount of investment in the technology directly, both through advance market commitments and through advance purchases of carbon removal by a variety of companies across a spectrum of industries and sizes. Motivations for these purchases are not well documented, but potential motivations can be identified. Many companies have goals of reaching net zero emissions by a certain date and may want to start building relationships with CDR providers that have proven, durable, measurable techniques for removal, as referenced by Stripe [85] and Microsoft [18] in their Climeworks press releases. As several of the companies making these early investments are tech companies, part of the motivation may also come from branding as being forward-thinking, technology-focused companies, which aligns well with the DAC technology.

DAC with utilization is also providing a connection between DAC consumers and DAC providers at present. While not discussed heavily in this thesis, these niche applications of

DAC technology for the creation of products beyond carbon removal help to lower the overall cost of DAC processes until DAC carbon removal as a service is more accessible to a larger group of consumers. This is consistent with what was seen in the scale-up and cost-reduction path of solar PV, where niche applications were found for a product due to its scalability and flexibility until the ultimate goal could be reached.

5.4 Acceleration Considerations for Key Stakeholders

Learnings from Sections 5.1 and 5.2 can be combined to help address Research Question 2. Table 4.1 shows a number of opportunities for each DAC method to align closer with a desired analog cost reduction behavior, indicated in the table with a yellow box and the letter "O". Many of these are architectural decisions as discussed in Section 5.2, but others can be controlled beyond these initial product design choices by various stakeholders in the DAC ecosystem.

5.4.1 DAC Providers

Many of the options available to the DAC companies regarding the product they are pursuing are specific to early design choices discussed in Section 5.2. However, there are additional actions DAC providers can consider pursuing to accelerate momentum toward cost reductions.

One of these actions is community engagement, both in the local areas companies plan to operate in and in the larger political systems of countries where they operate. Concerns could arise within communities locally when DAC plants are being planned for an area including but not limited to low levels of CO_2 on ecosystems near the facilities, water usage by the facility depending on the DAC method used by the plant, or pipelines associated with transporting the captured CO_2 to storage locations. By listening to community concerns and needs early, DAC providers can integrate them into project designs early on. Expanding general awareness and understanding of the technology and its risks can help build trust and relationships within the community. Smith et al. found in their review of public perceptions of CDR that general awareness is low and awareness of novel techniques like DAC is even lower [96], providing an opportunity for the industry to educate the public. This action would support the "appealing to the public" factor described in the solar PV cost reduction drivers table and would benefit any DAC method, regardless of if it was found to be analogous to solar PV. For concerns like low levels of CO_2 on the surrounding area, DAC providers could work with universities or third parties in advance to study these impacts if limited research is available.

Another action that could be taken by DAC providers is early collaboration across companies to find opportunities for standardization of system components. Despite the lack of convergence on a common design, there may be similar parts or inputs across technologies that could allow for early acceleration of manufacturing scaling. The sorbent for S-DAC, in particular, makes up a significant portion of the system cost. If more providers use a common sorbent, economies of scale in manufacturing that material could be very impactful. Further, this could be an area to look for opportunities for small efficiency losses that lead to high-cost reductions, perhaps in the purity or performance expectations of the sorbent. For example, if the sorbent could be produced at much lower costs by lowering its life expectations, the additional cost from buying it more frequently could be offset by the overall lower cost, especially since this could then drive larger economies of scale in its production.

While they are not directly DAC providers, organizations like the DAC coalition could play an important role in driving some of these behaviors within the DAC provider community. They could work to organize all of the players to find these opportunities for cross-company alignment on a sorbent or acceptable efficiency-cost tradeoffs. They could also organize studies to better understand the impacts of pursuing these types of ideas, whether with universities or third-party contractors, without bias to any one DAC method. Participation of DAC providers in industry-wide conferences like the DAC Summit can enable knowledge transfer and relationship building within the community as well.

5.4.2 DAC Buyers

Companies and individuals within the private sector may have more influence in the scale-up of these DAC methods than one would initially think. As discussed in Section 5.3, many companies are taking an active role early on in the DAC market. As motivations for participating in the market may vary across company strategies, desired outcomes may vary as well.

Regardless of the motivation behind investing in DAC at a high cost, there are some actions that make sense for buyers to consider across the board. One such action is to focus on purchases with companies that can provide a clear roadmap of how their DAC method will be lowered to achieve more accessible costs long-term. Frontier is a good example of a purchaser with this behavior, so it is apparent to any company hoping to sell carbon removal exactly what requirements must be met [28]. This can drive DAC supplier behavior to create clear plans for how their method will reduce costs over time.

5.4.3 Governments and Policymakers

There is a large amount of literature available proposing actions governments should take to address climate change, ranging from the commonly suggested global carbon tax to detailed local-level policies. This level of policy analysis is outside the scope of this thesis. However, there are a couple of policy suggestions that are supported by the analysis completed.

One action the public sector could take to accelerate the scale-up and cost reduction of DAC specifically is carbon removal procurement based on the example of solar PV. This would directly influence the scale-up of the technology by ensuring demand within a given time period, budget, or capacity allocation. The value of this action is dependent on the continuity of policy, however, which can create a risk to companies that may have stranded assets if the political atmosphere changes.

Another concern with this approach is that a policy like this inherently "picks favorites", which can lead to poor overall market outcomes. If the policy was expanded to include all CDR techniques, DAC and other emerging novel CDR techniques may no longer compete on a cost basis [47]. With that in mind, one impactful near-term action policymakers could take is to work with experts at an international level to develop robust MRV and accounting standards for use across CDR techniques, as recommended by Smith et al. in the 2023 State of CDR report [96]. Development of these standards may be less susceptible to political discontinuities.

The main levers the U.S. government is currently taking toward direct air capture are competitive funding programs and subsidies through the 45Q tax credit. The competitive funding programs include both the DAC Hubs program and the DAC Prize discussed in Section 2.2.4. Given DAC's current immaturity, these programs could be a useful way to spur innovation across methods and provide young companies with the funds to advance their systems. By creating four full regional hubs, the government is assisting in creating the infrastructure associated with DAC at a large scale, which might be difficult for startups to accomplish on their own at the scale needed. This is a challenge that an analog like solar PV didn't face since the main infrastructure it needed to tie into was the power grid. Through these massive projects, supply chain systems may emerge that could drive down production costs across DAC methods if the development of the hubs is planned with this in mind.

What the competitive programs lack, however, is the full power of procurement policies that guarantee a market for the technology after the competition ends. If these programs accelerate enough scale-up to bring the DAC methods down the cost curve close enough to the 45Q tax credit, the LCFS trading credits, or a combination of the two, these may be enough to sustain the market alongside private purchases. It also inherently creates competition amongst DAC providers, which could lead to less knowledge sharing across companies and potentially impede technological learning at a domain level. Given the urgent need for cost reductions, though, this innovation-stimulating approach could be a useful policy lever overall.

5.5 Generalization of Results

This study has been specifically designed for DAC. However, there are some takeaways that could be useful for future studies. One such finding is the importance of considering if multiple methods under the same generalization merit separate analyses when using learning or improvement curves, as found for S-DAC and L-DAC for DAC technology. Another is the value in comparing across multiple analysis approaches when using learning or improvement curves. Cross-comparison can provide additional confidence in the results as inputs often come from a larger variety of sources.

In comparison to other studies focused on the eventual cost of DAC, the cost ranges found for S-DAC and L-DAC in 2050 are within the range seen in the literature (see Section 2.2.5. Across the learning rate analyses (excluding the analog scale-up scenarios), this study found a range of about \$100-\$400/tonCO_2 for S-DAC and a range of \$100-\$220/tonCO_2 for L-DAC. A much wider range was seen for both methods using improvement rates, but given the 25-year timeframe, improvement rate analysis results are less reliable in 2050. The National Academies of Sciences, Engineering, and Medicine report a range of \$89-\$407/tonCO_2 net for S-DAC and \$156-\$506/tonCO_2 for L-DAC [80].

One reason for the difference in L-DAC ranges between that study and this is their inclusion of a case where hydrogen is used for thermal energy and another where coal is the electricity source, which increases the high-end estimate from \$357/tonCO_2 to \$506/tonCO_2.

The range is still on average higher for L-DAC, though, more in line with the sensitivity that considered L-DAC scale-up to be in line with natural gas scale-up, which predicted a 2050 cost of \$279/tonCO_2. The analog scale-up sensitivity cases were deemed too extreme and removed from the range, but perhaps in the case of L-DAC at least they should be considered.

5.6 Limitations of This Study

Certain limitations should be considered when reviewing this analysis.

As discussed in Section 2.3.1, many experts note that one-factor learning rate analyses are potentially an oversimplification and do not take into account the underlying drivers of cost reductions. This analysis makes heavy use of one-factor learning rates, particularly in the sensitivities considered. There was an attempt to address this by including the decomposition analyses. However, many of the same analogs were used at the component level as the one-factor level due to data availability. A future improvement could be expanding the component analyses to include sensitivities if enough reliable analog data could be gathered.

To build on that, ideally, a full analog study would have been completed for each component of the decomposition analysis. However, this was unrealistic, given time constraints and data availability. This could be another future improvement to the study.

Other limitations involve simplifications that were made on inputs for the analysis. One such shortcoming is that compression, transportation, and storage costs are assumed to be fixed at \$15/tonCO_2. Given the level of uncertainty for these costs, the timing of meeting the cost thresholds discussed in this thesis could be impacted. It has also been noted by experts that the sequestration portion of this process, in particular, could become a bottleneck for CCUS and DAC deployment due to predicted slow improvement rates [95], which has not been accounted for in this study.

One final caveat for this study is regarding cost versus price. This has already been discussed in Section 3.2.1 but is worth reiterating. Initial costs for S-DAC are truly initial prices since the carbon removal price from Stripe's purchase is the reference point. From a cost-to-operate perspective, the cost thresholds may be reached faster than indicated in the results since some margin is likely included in this initial price.

Chapter 6

Conclusions and Future Work

This study demonstrates the value of considering the different DAC methods separately when considering initial and eventual cost estimates. It begins by describing why carbon removal and direct air capture are important in the efforts to limit climate change and ground the study with research questions of interest in the Introduction chapter. The Literature Review provides relevant context for CDR, DAC, and technological change theory. The framework and inputs for the analysis are laid out in the Method and Framework chapter and results are displayed in the following chapter. Finally, these results are discussed and the research questions are examined for insights from the study in the Discussion chapter. This chapter will provide conclusions for the analysis and outline opportunities for future work.

This study found a range of about \$100-\$400/tonCO_2 for S-DAC and \$100-\$220/tonCO_2 for L-DAC using learning curves across a variety of scenarios. This range is within the ranges seen across the literature. It further supports the growing body of work that shows DAC is capable of reaching costs that would compete with other CDR techniques and hard-to-abate mitigation costs.

Through a comprehensive exploration of outcomes using both single-factor and component-based approaches for learning and improvement curves, a deeper understanding of the potential range of cost reduction forecasts through 2050 emerges, surpassing the insights gained from a singular approach. Learning curve results were deemed the most reliable among these approaches for the 25-year window studied, but consistency across the learning and improvement rate analyses in the early time periods of the analysis supports the findings of Nagy et al. in their study comparing the two approaches [79]. Limitations to the approaches used do exist, however, and should be considered.

This study can be a building block for future work in this field. Once the less mature DAC methods reach the pilot and commercialization stage, the analog assessment from this study can help build learning or improvement rate analyses. Further, a patent analysis specifically for DAC could be performed to see how improvement rate predictions at an industry level compare to the S-DAC and L-DAC predictions. Once actual the first commercial L-DAC plant comes online, it would also be prudent to rerun the L-DAC portion of the cost reduction analysis with actual initial L-DAC costs rather than detailed estimates.

The final takeaway from this study to reiterate is the suite of actions described for the major stakeholders in the DAC ecosystem to help accelerate scale-up and cost reduction. Policymakers can provide impact by developing standards for MRV and accounting in CDR.

The private sector can set clear requirements for carbon removal purchases, focused on purchasing proven, durable, measurable techniques that, in the case of DAC, can provide clear paths for cost reduction to more accessible levels. Finally, DAC providers themselves can focus on early design choices that enable cost reductions and work together towards economies of scale in manufacturing.

To meet the Paris Temperature Goals, the world will need a suite of CDR techniques available by mid-century. Direct air capture is a promising option, if it can scale and reduce costs at rates fast enough to meet demand. This thesis suggests this is achievable with both mature DAC methods and provides additional levers stakeholders can utilize to accelerate this goal.

Appendix A

Decomposition Analysis Details

This appendix includes the component-level cost breakdown for the curves found in Section 4.2.2. The LR & IR used for each component and the corresponding analog can be found in Tables A.1 and A.2. Components marked as "Minimal" in the analog column indicate that minimal learning is expected due to this already being a mature component. Analogs are based on the author's best judgment from available data.

The resulting cost breakdown for each DAC method by approach can be found in Figures A.1 and A.2 for S-DAC and Figures A.3 and A.4 for L-DAC.

		LR Analysis			IR Analysis		
	Component	Analog	LR	Source	Analog	IR	Source
CAPEX	Adsorbent	Solar	23%	[89]	Adsorption IR	12%	[95]
	Blower	Minimal	1%	-	Minimal	1%	-
	Vacuum Pump	Minimal	1%	-	Minimal	1%	-
	Condenser	Minimal	1%	-	Minimal	1%	-
	Contactor	Solar	23%	[89]	Solar	9%	[5]
OPEX	Adsorption	Solar	23%	[89]	Adsorption IR	12%	[95]
	Steam	Minimal	1%	-	Minimal	1%	-
	Vacuum Pump	Minimal	1%	-	Minimal	1%	-
Offset	Generated CO2	Solar	23%	[89]	IGCC+CCS	7%	[95]

Table A.1: Learning and improvement rates used for S-DAC component analysis

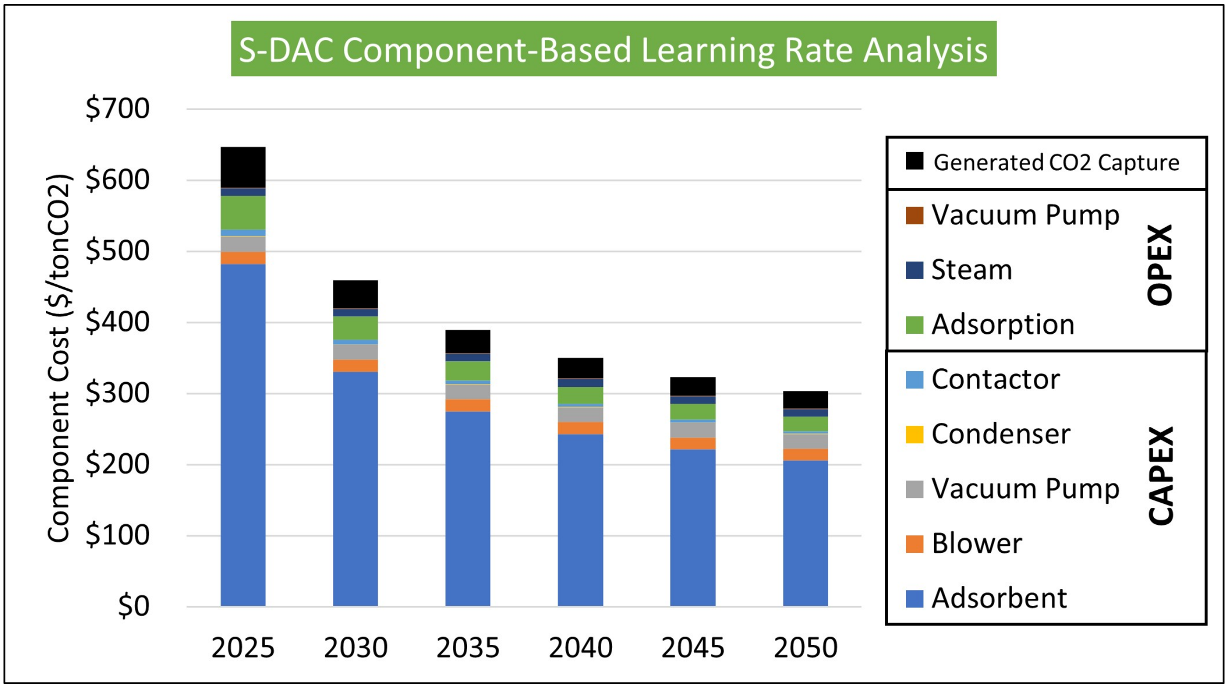

Figure A.1: Cost breakdown at the component level for S-DAC learning rate component analysis

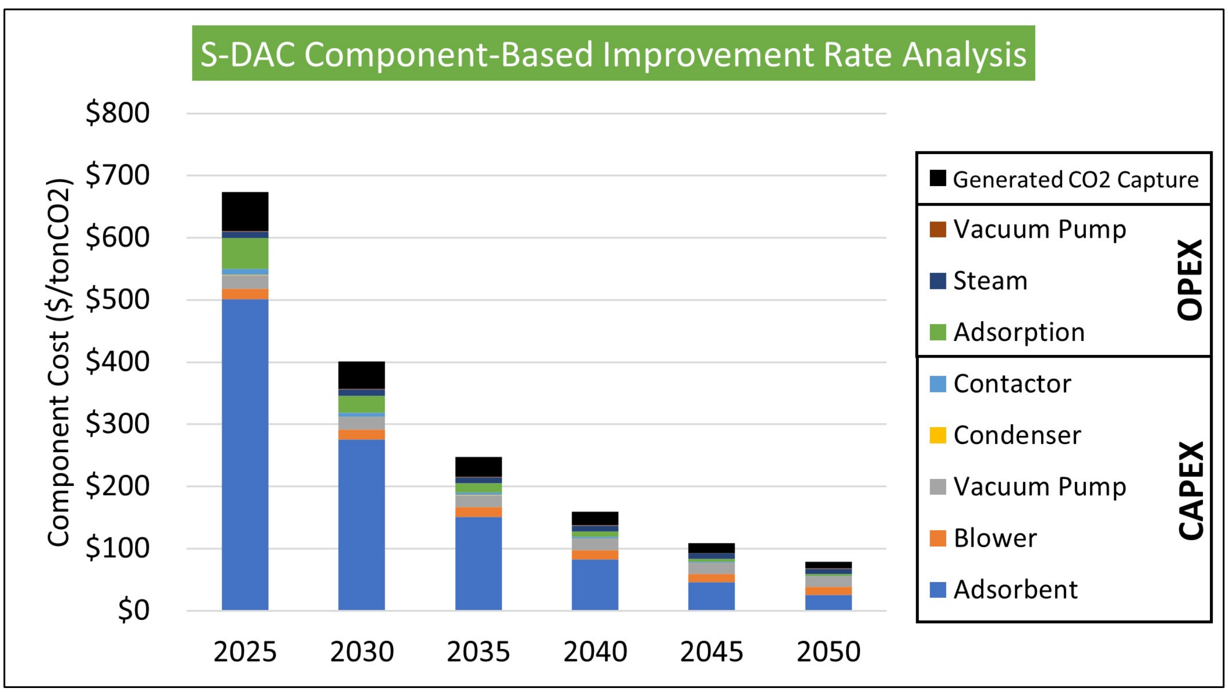

Figure A.2: Cost breakdown at the component level for S-DAC improvement rate component analysis

		LR Analysis			IR Analysis		
	Component	Analog	LR	Source	Analog	IR	Source
CAPEX	Contactor Array	NG (CAPEX)	10%	[90]	NGCC	7%	[5]
	ASU&C	NG (CAPEX)	10%	[90]	NGCC	7%	[5]
	SCC	NG (CAPEX)	10%	[90]	NGCC	7%	[5]
	OF Calciner	NG (CAPEX)	10%	[90]	NGCC	7%	[5]
OPEX	Maintenance	NG (OPEX)	6%	[90]	Minimal	1%	-
	Labor	Minimal	1%	-	Minimal	1%	-
	Makeup & WR	Minimal	1%	-	Minimal	1%	-
	Electricity	Minimal	1%	-	Minimal	1%	-
	Thermal Energy	NG (OPEX)	6%	[90]	NGCC	8%	-
Offset	Generated CO2	NG (OPEX)	6%	[90]	IGCC+CCS	7%	[95]

Table A.2: Learning and improvement rates used for L-DAC component analysis

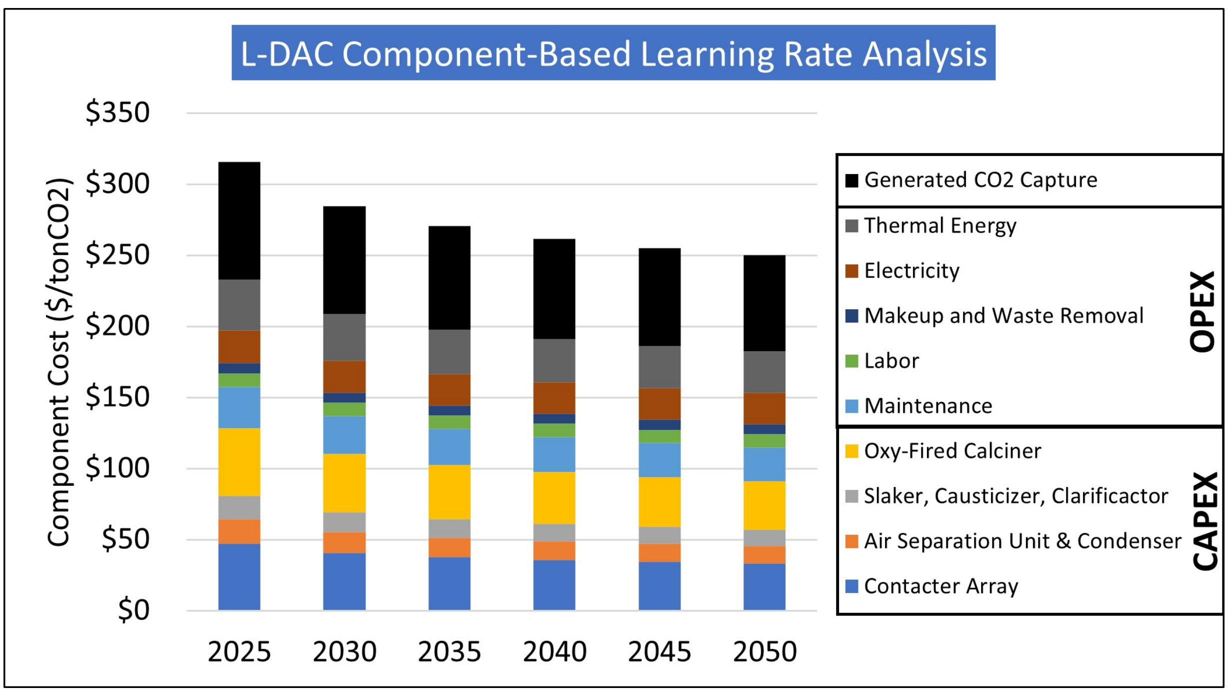

Figure A.3: Cost breakdown at the component level for L-DAC learning rate component analysis

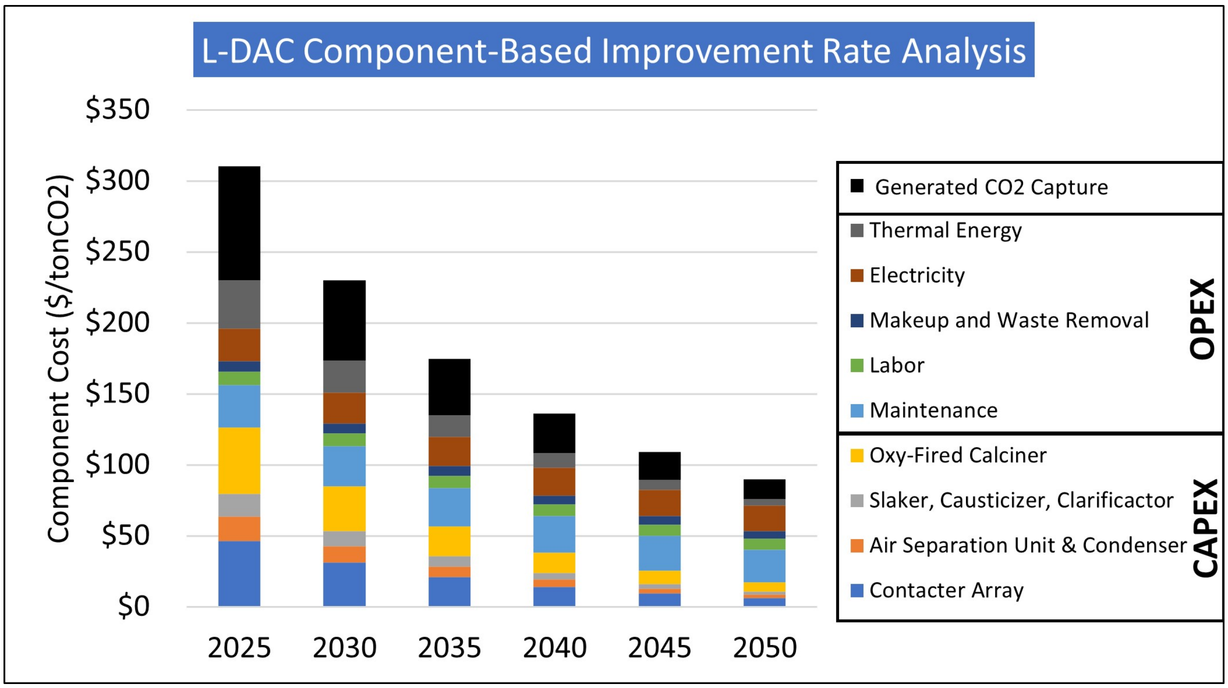

Figure A.4: Cost breakdown at the component level for L-DAC improvement rate component analysis

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