Supplementary Material for

Costs to achieve target net emissions reductions in the U.S. electric sector using direct air capture

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Aqueous Kraft Process-based direct air capture configuration

Figure S1. Major processes and material flows of a direct air capture plant that annually captures 1.06 Mt of CO\textsubscript{2} from air. The CO\textsubscript{2} concentration in the air is assumed to be 500 ppm. This figure is based on the process flow and conditions described in (Socolow et al 2011) and (Baciocchi et al 2006 – adapted from Baciocchi R, Storti G and Mazzotti M 2006 Process design and energy requirements for the capture of carbon dioxide from air Chemical Engineering and Processing: Process Intensification 45 1047–58, Copyright 2006, with permission from Elsevier.

The reference Kraft process-based direct air capture (DAC) plant (Figure S1) is fundamentally based on the design adopted in the American Physical Society study (Socolow et al 2011). We update this reference DAC design based on recent publications, which are discussed in the next paragraph. (Socolow et al 2011) assumed 330 DAC units, each capturing 3.21 kt of CO\textsubscript{2} as investigated by Baciocchi et al. in 2006, collectively removing 1.06 Mt of CO\textsubscript{2} annually. Fans blow about 270 million m\textsuperscript{3} of air per hour through plastic packing structure where strong alkaline solution selectively absorb half of the CO\textsubscript{2} from the air. The captured CO\textsubscript{2} is precipitated as CaCO\textsubscript{3} which is thermally decomposed to generate pure stream of CO\textsubscript{2}. In the calciner, natural gas is combusted with pure oxygen produced on-site to provide 8.07 GJ of thermal energy needed to capture one tonne of CO\textsubscript{2} from air. This generates additional 0.413 tonnes of CO\textsubscript{2} per tonne of CO\textsubscript{2} captured from air, all of which is captured, compressed to 150 bar, and assumed to be permanently stored underground along with CO\textsubscript{2} captured from air. As a result, this 1 Mt-scale DAC plant captures roughly 1.5 Mt of CO\textsubscript{2} every year.

Updates to the process described in (Socolow et al 2011) include the following. First, we assume stainless steel packing material can be replaced with plastic packing to reduce the cost. This design modification help reduce the overall capital cost by 33% without sacrificing system performance (Zeman 2014, Holmes and Keith 2012). Second, we update the energy required to compress and store captured CO\textsubscript{2} using an 8-stage centrifugal, integral gear compressor and injecting CO\textsubscript{2} underground at 150 bar (National Energy Technology Laboratory 2018). The updated calculation also includes additional injection energy needed to replace ground water with injected CO\textsubscript{2}, which is estimated to be around 1.5 kJ per mol CO\textsubscript{2} injected (House et al 2011). As a result, 0.588 GJ of energy is needed to compress and inject both CO\textsubscript{2} originating from air and natural gas combustion.
underground for every tonne of CO$_2$ captured from air. Replacing the original compression energy calculated in the APS report with this value, and accounting for all the energy required to operate DAC, about 1.94 GJ of grid electricity is used to capture 1 tonne of CO$_2$ from air using the DAC plant. This total electricity requirement includes energy needed to run the fans in the absorbers, pump liquids, convey pellets, generate oxygen with air separation unit, and operate the compressor. Electricity calculation includes electricity needed to process both CO$_2$ originating from air and on-site natural gas combustion. Further details are provided in Section 4.

2 Input parameters, assumptions, LETSACT model code, and result files

The following link (https://umich.box.com/s/fa6g7j3hy0sdo2pu1ycq8q3eay1e7hhb) provides access to the model input file, code, and result files generated for the analysis in this paper. This is a public link and does not require subscription or sign-in for Box. Table S1 provides additional details about assumptions and data sources.

Table S1. Input parameters and assumptions for EGUs and DAC plants in the U.S. electricity sector. This is an updated version of Table S4 from (Supekar and Skerlos 2017a). Adapted with permission from Supekar S D and Skerlos S J 2017 Analysis of Costs and Time Frame for Reducing CO$_2$ Emissions by 70% in the U.S. Auto and Energy Sectors by 2050 Environmental Science & Technology 51 10932–42. Copyright 2017 American Chemical Society.

| Parameters | Values/Assumptions/Sources |
|------------|-----------------------------|
| Age-wise distribution of 2014 initial stock | Data of installed capacity, generation, and age of generators obtained from the NEEDS dataset; generation capacity older than 70 years, which comprised 3% of total capacity, is excluded (U.S. Environmental Protection Agency 2015, 2016, U.S. Energy Information Administration 2017b); DAC plants are assumed to be available starting 2015 and no initial fleet exists in 2014 |
| Capacity discard probability | Assumed as a step function with discard probability = 0 until the expected service life of the technology, and = 1 beyond that. |
| Maximum service life | Assumed 60 years for PC, NGCC, PC-CCS, NGCC-CCS, N, and H; 40 years for NGGT, P, and G; 30 years for B, W, SPV, and STH; 25 years for DAC (Carbon Engineering n.d.) |
| Deployment & O&M costs, capacity factors | EGU costs are obtained from (Black & Veatch 2012, U.S. Energy Information Administration 2016, Lazard 2016). Capital cost of DAC is assumed to decrease by 15% in year 2027 from learning. Cost assumptions for DAC are outlined in Table S4. 90% of capacity factor is assumed for DAC in all uncertainty levels. |
| Capacity retirement cost | Retirement costs are comprised of the cost of any remaining capital liability assuming a financing period of 20 years, and a total interest rate of 20% comprised of 3% risk, 12% return on investment/equity, and 5% tax. |
| Heat rates | EGU heat rates are obtained from (Black & Veatch 2012, U.S. Energy Information Administration 2016, Lazard 2016). For DAC, heat rate is defined as the ratio of thermal energy demand with respect to electricity demand as shown in Table S4. |
| Emission factors | Emission factors for EGUs are calculated based on heat rates and carbon content of fuels as specified in (U.S. Environmental Protection... |
Electricity demand of three 1 Mt-scale DAC plant designs used to calculate three uncertainty levels as shown in Table S4.

Fuel & electricity costs
Fuel prices and electricity costs are treated exogenously and obtained from the U.S. Annual Energy Outlook data for 2016 (U.S. Energy Information Administration 2017a).

Relative market penetration of different renewables
The relative capacity addition of new W, STH, SPV, and G plants follow a fixed proportion which reflect the resource availability and its distribution over the entire U.S.; The W:STH:SPV:G ratio is 1:0.1:0.1:0.03 for low case, 1:0.25:0.25:0.03 for nominal case, and 1:0.5:0.5:0.03 for high case (Jacobson and Delucchi 2011, MacDonald et al 2016).

3 Setup of uncertainty scenarios for the LETSACT model
Input parameters with uncertainty ranges are grouped into 3 parameter sets as outlined in Table S2. Each of these parameter sets are allowed for three uncertainty levels, which collectively define 27 uncertainty scenarios as listed in Table S3. Then the LETSACT model generates unique set of optimized results using the diverse set of input parameters.

Table S2. Three sets of input parameters that uniquely define 27 uncertainty scenarios. This is an updated table of Table 1 from (Supekar and Skerlos 2017a). Adapted with permission from Supekar S D and Skerlos S J 2017 Analysis of Costs and Time Frame for Reducing CO$_2$ Emissions by 70% in the U.S. Auto and Energy Sectors by 2050 Environmental Science & Technology 51 10932–42. Copyright 2017 American Chemical Society.

| Parameter set | Input parameters included in a set |
|---------------|-----------------------------------|
| A) Costs      | Power plant capital, O&M, retirement costs; fuel and electricity prices; revenues from electricity sales; capacity factors; relative capacity addition ratios between renewables |
| B) Emissions  | Power plant thermal efficiency; decrease in efficiency with aging; carbon intensity of plants; upper limit for new capacity addition of pulverized coal plants |
| C) Demand     | projected electricity demand |

Table S3. The uncertainty levels for each of the uncertainty categories (0 = Low, 1 = Nominal, 2 = High). This is an updated table of Table S1 from Supekar and Skerlos 2017. Adapted with permission from Supekar S D and Skerlos S J 2017 Analysis of Costs and Time Frame for Reducing CO$_2$ Emissions by 70% in the U.S. Auto and Energy Sectors by 2050 Environmental Science & Technology 51 10932–42. Copyright 2017 American Chemical Society.
4 Uncertainty in DAC characteristics and CO$_2$ storage potential

4.1 DAC characteristics

Since direct air capture plants are still in their pilot stage, significant uncertainties exist in their cost and energy requirements based on variabilities in process design, financial assumptions, and other factors. DAC costs range from 35-1,000 $/tCO$_2$ captured (House et al 2011, Lackner et al 2012, Socolow et al 2011, Mazzotti et al 2013, Keith 2009, Lackner 2010, Zeman 2014, Keith et al 2006, Stolaroff et al 2008). One of the most commonly cited calculations is the APS study estimate, which concluded that DAC system will optimistically cost around 610 $/tCO$_2$. Subsequent studies (Zeman 2014, Holmes and Keith 2012) have pointed out that some of the design assumptions made in the APS study were not realistic and the cost can be reduced to 309-343 $/tCO$_2$ with different design choices. More recently, Carbon Engineering, a Canadian DAC startup developing similar Kraft process-based DAC, published their engineering calculation of 1Mt scale commercial DAC plant which shows lower energy requirement and cost compared to previous estimates (Keith et al 2018). On the other hand, House (2011) argue that overall cost of DAC will be much higher, on the order of 1,000 $/tCO$_2$, based on the trend of decreasing 2$^{nd}$ law efficiency with decreasing concentration as described by the Sherwood plot.

In this study, we develop three DAC plant designs and their corresponding energy, cost, and emissions estimates based on the ranges reported in the literature. These values are shown in Table S4, and are incorporated into the uncertainty scenarios described in the main body of the paper. The nominal case is based on a modified optimistic case of APS study as outlined in Section 1. The unmodified optimistic case from APS study set the high sensitivity case. The low case reflects energy balance and cost calculation proposed by Carbon Engineering. The cost of transporting and storing captured CO$_2$ is obtained from National Energy Technology Laboratory (NETL) study (Grant et al 2017) where the cost uncertainty identified in the report for each of the four major storage basins in the U.S.—Illinois, Williston, East Texas, and Powder River basins—is included in the analysis. The electricity and cost associated with operating DAC considers both CO$_2$ captured from air and CO$_2$ generated by natural gas combustion. In Table S4, these values are normalized per tonne of CO$_2$ captured from air.

Table S4. Energy, cost, and emission profiles of three DAC plant designs used to setup uncertainty range. Values under 'original DAC parameters' are used to generate variables listed under 'DAC parameters as 'reverse power plant'' that are used as inputs to the LETSACT model.

| Original DAC Parameters | Units$^a$ | Low | Nominal | High |
|-------------------------|----------|-----|---------|------|
| Representative Case     | State-of-the-art design (Keith et al 2018) Scenario C | Optimized design (Socolow et al 2011, Zeman 2014) | Non-optimized design (Socolow et al 2011) – Ideal case |
| Annual capture capacity | MtCO$_2$/year | 0.98 | 1.06 | 1.06 |
| DAC plant electricity use | GJ/tCO$_2$ captured | 1.32 | 1.94 | 1.94 |
### DAC Sensitivity

| Original DAC Parameters | Units\(^a\) | Low     | Nominal | High    |
|-------------------------|------------|---------|---------|---------|
| DAC plant NG use        | GJ/tCO\(_2\) captured | 5.25    | 8.07    | 8.07    |
| Derived 2nd law efficiency | %           | 11.8%   | 7.75%   | 7.75%   |
| Capital cost            | mil $      | 680     | 1,430   | 2,160   |
| Fixed O&M cost\(^b\)    | mil $/year | 26.5    | 55.8    | 84      |
| Non-fuel Operating cost\(^c\) | mil $/year | 4       | 4       | 4       |
| CO\(_2\) transportation & storage cost\(^d\) | $/tCO\(_2\) captured | 36.7    | 42.7    | 126     |

### DAC Parameters as “Reverse Power Plant”

| Nominal Capacity | MW   | -40.9  | -65.4  | -65.4  |
| Pseudo Heat Rate | Btu/kWh | -13,600 | -14,200 | -14,200 |
| Carbon Intensity | tCO\(_2\)/MWh | 2.73    | 1.85    | 1.85    |
| Capital Cost     | $/kW  | 16,600  | 21,900  | 33,000  |
| Fixed O&M        | $/kW-year | 659    | 857     | 1,290   |
| Variable O&M excluding purchased electricity\(^e\) | $/MWh | 47.6    | 50.1    | 133     |

\(^a\) Energy and cost profiles of a DAC plant consider processing and storing CO\(_2\) originating from both air and natural gas. These values are normalized by a tonne of CO\(_2\) captured from air, denoted by ‘tCO\(_2\)’.

\(^b\) Fixed O&M cost is assumed to be 3.9% of the capital cost, where maintenance costs 3% of the capital cost and labor costs 30% of the maintenance cost (Socolow et al 2011).

\(^c\) The non-fuel operating cost includes cost of makeup water and chemicals during the operation of DAC.

\(^d\) Assumes cost of transporting and storing captured CO\(_2\), including CO\(_2\) originating from air and natural gas combustion, in four major basins in the U.S. This cost is normalized by a tonne of CO\(_2\) captured from air. CO\(_2\) is transported via 100 km dedicated pipelines. Cost of storage at each basin is weighted with its total storage capacity to yield national average value, assuming a minimum CO\(_2\) storage of 50 Gt. Cost includes siting, permitting, and well monitoring costs.

\(^e\) Variable O&M cost includes non-fuel operating cost and CO\(_2\) transportation & storage cost.

### 4.2 CO\(_2\) storage potential

(Grant et al 2017) estimate the total U.S. CO\(_2\) storage potential to be between 413 – 448 Gt corresponding to a minimum CO\(_2\) storage value of 25 – 75 Gt at each of the four storage basins listed above. This storage resource estimate from the NETL study is an order of magnitude larger than the highest estimate for the amount of CO\(_2\) storage from DAC plants as determined by the LETSACT model in our analysis (about 25 Gt CO\(_2\) by 2050). It is therefore unlikely that CO\(_2\) storage in a DAC-based CO\(_2\) mitigation scenario would exceed the total CO\(_2\) storage capacity. However, this analysis does not include CO\(_2\) storage that may be needed if other negative emissions technologies (NETs) such as bioenergy with CCS are deployed at large scales. A separate analysis that is outside the scope of this paper would be needed to ascertain whether the strategic deployment of several NETs would run afoul of the CO\(_2\) storage limits.
5 Details of DAC integration into the LETSACT model

To integrate DAC plants into the LETSACT model, we model it with negative nominal capacity and heat rate. The negative nominal capacity indicates that DAC plants consume grid electricity to run fans, pumps, air separation units, compressors, and other auxiliary devices as opposed to generating electricity. This concept is shown in Figure S2, where DAC plants act as “reverse EGUs.” The negative heat rate for DAC plants is expressed in equation (S1), and it is the ratio of thermal energy demand \( \dot{Q}_{DAC} \) to electrical energy demand \( \dot{W}_{DAC} \) of a DAC plant. In the LETSACT model, this heat rate is used to estimate cost incurred from natural gas use in DAC plants, as shown in equation (S2), by multiplying it with natural gas price.

![Figure S2](image-url)

**Equation (S1)**

\[
HR_{DAC} \left( \frac{Btu}{kWh} \right) = -3412 \left( \frac{Btu}{kWh} \right) \cdot \frac{\dot{Q}_{DAC}}{\dot{W}_{DAC}} \cdot \frac{GJ_{\text{el}}}{tCO_2} \quad \text{(S1)}
\]

**Equation (S2)**

\[
FuelCost_{DAC} \left( \frac{\$}{MWh} \right) = -1 \cdot NG\text{price} \left( \frac{\$}{MMBtu} \right) \cdot \frac{HR_{DAC} \cdot 10^{-6} \left( \frac{MMBtu}{kWh} \right)}{10^{-3} \left( \frac{MWh}{kWh} \right)} \quad \text{(S2)}
\]
6 Energy and carbon balance of the grid-connected direct air capture plants

The net amount of CO₂ removed with DAC should account for the additional CO₂ emitted from its energy sources. In our DAC design, CO₂ generated from onsite natural gas combustion are captured and stored alongside air-captured CO₂ and does not contribute to additional emissions. However, additional CO₂ is emitted remotely from operating grid to power DAC plants. As a result, the net CO₂ removal rate of a DAC plant decreases with increasing grid carbon intensity. Thus, a DAC plant needs to scale up to achieve the designed removal rate. But this ramp-up entails additional electricity use which only results in more emissions. This positive feedback is inherent to carbon capture facilities that operate on power sources that emit additional carbon emissions; the operation of CO₂ capture units result in additional emissions associated with the increased use of fuels (Supekar and Skerlos 2015, 2017b). Figure S3 shows this feedback loop for DAC plants.

Figure S3. Mass and energy feedback loop inherent to capturing CO₂ from the air with DAC plants powered by electric infrastructure. The total amount of electricity needed to achieve the target CO₂ removal rate can be calculated by summing incremental electricity needed to scale up DAC until the target removal rate is achieved.

Thus, the total amount of energy required to remove the desired amount of CO₂ from air can be calculated in a recursive fashion as shown in Figure S3. We let \( \dot{m} \) be a mass flow of CO₂ where positive values represent emissions and negative values represent removal. We can also define \( \hat{\epsilon}_{DAC}, \hat{\epsilon}_{grid} \) as carbon intensity of DAC and electric grid respectively, in terms of tonne of CO₂ removed/emitted per MWh of electricity use/generation. We let \( \dot{W}_i \) be the electricity needed to operate a DAC plant at \( i \)th recursion. At the initial iteration \( (i = 0) \), we assume that grid-emissions are zero and that we can remove the target amount of CO₂ through operating a DAC plant \( (\dot{m}^{CO₂}_{goal} = \dot{m}^{CO₂}_{DAC0}) \). But considering non-zero emissions from grid, the net amount of removed CO₂ becomes \( \dot{W}_0 \cdot (\hat{\epsilon}_{DAC} + \hat{\epsilon}_{grid}) \). To achieve the target removal rate, we need to scale up CO₂ removal rate with DAC to compensate for the additional emissions from grid, \( \dot{W}_0 \hat{\epsilon}_{grid} \). The additional electricity requirement is \( \dot{W}_1 = -\dot{W}_0 \cdot \frac{\hat{\epsilon}_{grid}}{\hat{\epsilon}_{DAC}} \). But since this creates even further emissions from grid, the total amount of electricity required to meet the target removal rate can be expressed as an
infinite sum as seen in equation (S3). This infinite sum converges only when $\left| \frac{\hat{c}_{\text{grid}}}{\hat{c}_{\text{DAC}}} \right| < 1$. We find that equation (S3) converges in all of the three uncertainty cases of DAC. 

$$\tilde{W}_{\text{total}} = \lim_{n \to \infty} W_0 \cdot \left\{ 1 + \left( -\frac{\hat{c}_{\text{grid}}}{\hat{c}_{\text{DAC}}} \right) + \left( -\frac{\hat{c}_{\text{grid}}}{\hat{c}_{\text{DAC}}} \right)^2 + \cdots + \left( -\frac{\hat{c}_{\text{grid}}}{\hat{c}_{\text{DAC}}} \right)^n \right\} = W_0 \left( \frac{\hat{c}_{\text{DAC}}}{\hat{c}_{\text{DAC}} + \hat{c}_{\text{grid}}} \right)$$ (S3)

Figure S4A shows how effective CO$_2$ removal linearly decreases with increasing carbon intensity of the grid powering the DAC plants. Figure S4B shows how $\tilde{W}_{\text{total}}$ increases nonlinearly with increasing carbon intensity of the grid to achieve a fixed amount of CO$_2$ removal. When the grid carbon intensity is 0.6 tCO$_2$/MWh, close to the current level of the U.S. power grid, 48% more electricity is needed to remove 1 Mt of CO$_2$ from air with DAC compared to operating DAC with a zero-emission grid. Thus, the deployment of DAC plants is delayed in LETSACT model as long as possible to minimize total mitigation cost. The thicker portions in Figure S4 indicate the observed range of net CO$_2$ removal rate and net electricity demand of the DAC plants deployed in the LETSACT results. Typically, DAC plants deploy in LETSACT model when the additional electricity demand from positive emissions feedback fall below 6%.

7 CO$_2$ emissions constraint setup

In the climate action cases, the LETSACT model runs with an additional CO$_2$ emissions constraint which limits cumulative CO$_2$ emissions between 2015 and 2050 below the target emission level. This cumulative emission constraint, or CO$_2$ emissions budget, is defined as an area under a piecewise function that linearly decreases from the emissions level in 2010 to the target emissions level in 2050 after which is kept constant for additional 60 years. The additional 60 years consider
the service life of EGUs that are deployed in 2050 to ensure proper implementation of emissions constraint. Each point on the straight line represents an idealized annual CO$_2$ emission pathway of the U.S. electric sector. The actual emission trajectory may temporarily overshoot this ideal emission level as long as the excess emissions can be compensated later. Figure S5 compares the idealized emission constraint curve with a business-as-usual (BAU) emissions trajectory generated by the LETSACT model. The emissions trajectory from 2010 to 2014 is based on historic emissions (U.S. Environmental Protection Agency 2018) and LETSACT model generates emission trajectories from 2015 to 2050. As shown in Figure S5, the cumulative CO$_2$ emissions under BAU trajectory exceed carbon budget that reduced the annual emissions by 70% by 2050, as emission constraint is not imposed under BAU scenario.

Figure S5. CO$_2$ emissions constraint that reduces annual CO$_2$ emissions in 2050 to 70% below 2010 levels is compared to emissions trajectories generated with LETSACT model when no emissions constraint is imposed.

8 List of terminologies

Table S5. List of key terms used in this study and their descriptions.

| Terms                | Descriptions                                                                                                                                 |
|----------------------|-----------------------------------------------------------------------------------------------------------------------------------------------|
| Business-as-usual    | Business-as-usual case refers to the LETSACT model runs with the constraints defined by equations 2–3 and a nation-wide implementation of Renewable Portfolio Standard, but without the 2050 CO$_2$ emissions constraint defined by equation 4. An example of emissions pathway under business-as-usual is shown in Figure S6. |
| Climate action       | Climate action cases refer to the results generated by running the LETSACT model with all constraints defined by equations 2–4, including the 2050 CO$_2$ emissions constraint and a nation-wide implementation or Renewable Portfolio standard. Figure S6 shows an example emissions pathway. |
| Climate action year  | Climate action year is a year beyond which emissions constraint is activated. The LETSACT model runs without emissions constraint up to the year before climate action year, following a business-as-usual pathway. |
until before that year. Thus, starting with the climate action year, the LETSACT model runs with the 2050 CO\textsubscript{2} emissions constraint. Figure S6 shows emissions pathway under climate action year = 2026.

| Delayed climate action | Delayed climate action occurs when climate action initiates after 2015. In this case technology and emissions trajectory follows business-as-usual cases up until the year before climate action year. |
|------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Climate action timeframe | A collection of climate action years is called climate action timeframe.                                                                                                                              |
| Uncertainty scenarios  | Three parameter categories, each with three possible values, collectively generate 27 unique parameter sets. Each uncertainty scenario is then defined by one of these parameter sets and corresponding LETSACT results created by running the model using the chosen parameter values. As a result, 27 uncertainty scenarios are generated. |
| Fleet turnover          | Fleet turnover collectively represents new EGU additions, early EGU retirements decommission, and retirement of EGUs after their typical service life.                                               |
| Emission trajectory     | Emission trajectory denotes the annual trend in total CO\textsubscript{2} emissions generated from the U.S. electric sector as a result of running the LETSACT model. Example emission trajectories are shown in Figure S6. |
| Technology trajectory   | Technology trajectory collectively refers to the EGU stocks and flows over a certain period of time. An example of a technology trajectory is shown in Figure 4.                                      |
| CO\textsubscript{2} budget | A sector-specific CO\textsubscript{2} budget used in this study refers to the amount of cumulative CO\textsubscript{2} emissions corresponding to the 70\% emissions reduction in the U.S. electric sector by 2050 compared to 2010. The CO\textsubscript{2} budget is shown in Figure S5 as a blue area below straight emission curve. |

![Figure S6. Visual illustration of the terminologies listed in Table S5. CAY denotes climate action year. Since climate action initiates beyond 2015, this example scenario describes a delayed climate action.](image_url)
9 Additional figures on technology evolution and fuel use

9.1 Retirement under DAC-based climate action versus preventive climate action

Figure S7. Delayed climate action with DAC leads to the retirement of the same set of EGUs as in the case of preventive climate action without DAC, as marked in black. Delayed climate action leads to additional retirement of fossil fuel EGUs as marked in red, particular newer EGUs in the case of DAC-based delayed climate action.

9.2 Example technology trajectory with NGCC–CCS as a low-carbon EGU technology

Figure S8. Least-cost technology trajectories under a. BAU; b. climate action starting in 2020; and c. climate action starting in 2035 for a sample uncertainty scenario featuring natural gas combined cycle with CCS (NGCC-CCS) as a low-carbon EGU technology. Roughly 25% of all uncertainty scenarios rely on NGCC-CCS along with renewables to meet 2050 emissions targets.
9.3 Changes in fuel use under climate action relative to business-as-usual

Figure S9. Difference in total fuel use through 2050 relative to business-as-usual (BAU) for climate action year a. 2020 and b. 2035 expressed in quadrillion Btus (quads) for different uncertainty scenarios. Natural gas use in a. is slightly higher than BAU in some scenarios due to a higher penetration of NGCC (combined cycle) EGUs. Scenarios in b. showing increased non-DAC natural gas use rely on NGCC–CCS EGUs to supply low-carbon electricity in addition to renewables.
10 Results from additional model runs

10.1 4% and 10% discount rates

Figure S10. a. Cumulative CO₂ emissions; b. annual CO₂ emissions; and c. DAC deployment under different climate action years with a 4% (a–c, left) and 10% (a–c, right) discount rate. Each individual curve or data point represents a single uncertainty scenario. Segments in c indicate the delay between start of climate action and actual deployment of DAC plants.
Figure S11. a. Climate action cost; b. total generation retired early through 2050; and c. total new generation added through 2050 as a function of climate action year with a 4% (a–c, left) and 10% (a–c, right) discount rate. Approximated Gaussian density distribution for each quantity in the left panels in a – c is shown in their respective right panels.
10.2 60% and 80% emission reduction targets

Figure S12. a. Cumulative CO₂ emissions; b. annual CO₂ emissions; and c. DAC deployment under different climate action years for a 60% (a–c, left) and 80% (a–c, right) emissions reduction by 2050. Each individual curve or data point represents a single uncertainty scenario. Segments in c indicate the delay between start of climate action and actual deployment of DAC plants.
Figure S13. a. Climate action cost; b. total generation retired early through 2050; and c. total new generation added through 2050 as a function of climate action year for a 60% (a–c, left) and 80% (a–c, right) emissions reduction by 2050. Approximated Gaussian density distribution for each quantity in the left panels in a – c is shown in their respective right panels.
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