Characterizing the effects of policy instruments on the future costs of carbon capture for coal power plants

Gregory F. Nemet · Erin Baker · Bob Barron · Samuel Harms

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Abstract We develop a methodology with which to assess the effects of policy instruments on the long-term abatement and costs of carbon capture and sequestration (CCS) technologies for coal power plants. Using an expert elicitation, historical data on the determinants of technological change in energy, and values from the engineering literature, and demand estimates from an integrated assessment model, we simulate ranges of outcomes between 2025 and 2095. We introduce probability distributions of all important parameters and propagate them through the model to generate probability distributions of electricity costs, abatement costs, and CO_2 avoided over time. Carbon pricing has larger effects than R&D and subsidies. But much of the range of outcomes is driven by uncertainty in other parameters, such as capital costs and returns to scale. Availability of other low

G.F. Nemet

La Follette School of Public Affairs, University of Wisconsin, USA

Tel.: +1-608-2653469

Fax: +1-608-2653233

E-mail: nemet@wisc.edu

carbon technologies, particularly bioenergy with CCS affects outcomes. Subsidies have the biggest impacts when they coincide with expanding manufacturing scale of CCS components. Our results point to 4 parameters for which much better information is needed for future work informing technology policy to address climate change: capital costs, demonstration plants, growth constraints, and knowledge spillovers among technologies.

Keywords Carbon capture · technological change · climate policy

1 Introduction

Carbon capture and storage (CCS) is potentially one of the most important technologies to address climate change (Kriegler et al 2014). CCS typically accounts for more substantial portions of future emissions reductions in integrated assessment modeling exercises (Koelbl et al 2014). Meeting emissions reductions targets without the availability of CCS would raise mitigation costs considerably, by some estimates on the order of trillions of dollars by mid-century (IEA 2012). However, CCS is only likely to contribute substantially to climate change mitigation if its costs are near or below the marginal cost of emissions abatement. Despite decades of research and maturity in the underlying components, no full scale power plant with CCS has yet been built, which is one reason why the future costs of CCS are open to a wide range of possibilities. Our approach is to combine expert elicitation with a bottom-up cost model to generate distributions of CCS costs under varying policy combinations.

1.1 The challenge for policymakers

Governments play a central role in the prospects for CCS due to the presence of multiple market failures. In addition to negative pollution externalities, knowledge spillovers associated with the development of new technologies create positive externalities; firms can free ride on the technology investments of others, e.g. by reverse engineering (Nemet 2013). As a result, governments perform their own R&D and subsidize others' R&D as well. Knowledge spillovers are also particularly problematic later in the process, when the scale of the investments required is large but when technical uncertainty is still high (Weyant 2011). Consider the decision about building a first of its kind nuclear power plant or carbon capture plant. Billions are at stake, no one knows how well it will work, and the whole world can watch whether it does. Providing incentives for these types of investments requires additional policies—such as subsidies for early demand—since even a perfectly priced carbon tax will not avoid the problem of knowledge spillovers. This paper thus looks at the effect of these 3 types of policy instruments: carbon pricing, R&D, and subsidies for early demand on CCS.

Multiple market failures, multiple policy instruments, and multiple technical pathways within CCS present policymakers with a complicated set of decisions. The effects of any of these specific policies on future technology performance are highly uncertain. The perspective here is that developing policies that are robust to broad set of possible future conditions requires explicit characterization of the anticipated performance of individual energy technologies. While technological change is inherently uncertain, we see recurring patterns when surveying cases together (Grubler and Wilson 2013): technologies improve via learning by doing and also by economies of scale (Nemet 2006, 2012b); flows of knowledge from one area of technology to another have been important (Nemet 2012a); and the outcomes of investments in innovation are typically highly skewed (Scherer and Harhoff 2000), with a small number of winners, a larger number of losers, and often very little basis with which to distinguish between the two before investments are made. Our approach is to make use of what we know about the historical dynamics in energy technologies to develop a model that adds some insight on the wide array of policy choices that policymakers may have at their disposal.

1.2 Technological change in CCS

Previous studies of CCS account for anticipated improvements in production using learning or experience curves (Rao et al 2006; Rubin et al 2007; van den Broek et al 2009; Magne et al 2010). Other notable papers in this domain include assessments of future CCS costs by: Hamilton (2009); Herzog (2011); Li et al (2012) and a review by Baker et al (2012). We incorporate important methodological developments from this work, including the observation that costs typically increase before declining and the disaggregation of costs so that different system components can improve at different rates (Rubin et al 2007). To more closely match the model with the empirical and theoretical bases for learning (Wright 1936; Arrow 1962) we introduce additional specificity on the mechanism by which learning occurs for each cost component.

Despite historical analogs and other models, the effect of research spending on technology outcomes remains particularly difficult to assess. For the outcomes of R&D, we use expert elicitation, a formal method with which to formulate probability distributions of outcome using the responses of experts to a series of questions. The National Research Council has specifically recommended using expert elicitation to inform government decisions about energy technologies (NRC 2007) and several elicitations have since been completed on on CCS (Baker et al 2009; Chung et al 2011; Chan et al 2011). In 2011 we conducted our own expert elicitation (Jenni et al 2013) with the specific intention of using the responses to populate the model described in the next section.

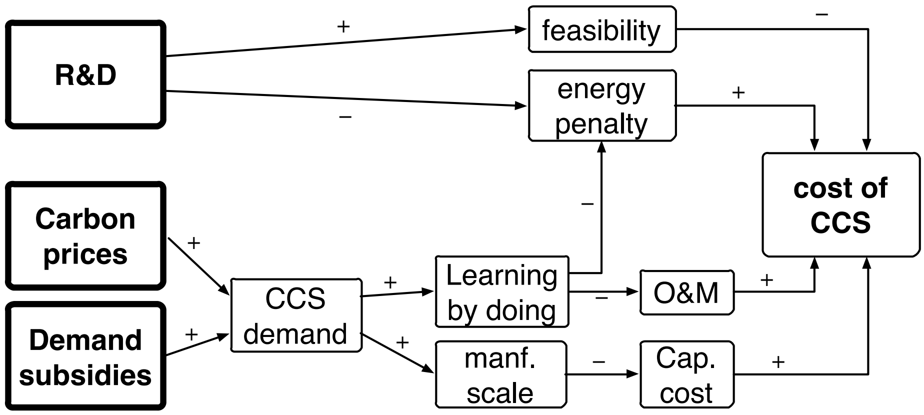

Fig. 1 Schematic of calculations of technological change for coal CCS.

2 Modeling approach

We model the cost and diffusion of CCS technology applied to coal power plants. The model is global and proceeds in 5-year increments from 2015 until 2095. It estimates the future cost and adoption of 7 types of coal-based CCS technologies. We make assumptions about demonstration plants from 2015-2020. Costs in 2025 are based on a combination of an expert elicitation of energy penalties (Jenni et al 2013) and a CCS cost model (Nemet et al 2013) that includes capital costs, operations and maintenance (O&M), and transportation and storage. Public R&D investment can reduce energy penalty of all CCS technologies and can improve the feasibility of advanced CCS technologies. After 2025, the technologies are available to be commercialized. They then improve due to learning by doing and economies of scale. Figure 1 provides a general overview of this sequence of calculations and how policy instruments affect them. Additional detail is provided in an Electronic Supplementary Material (ESM) document.

2.1 Costs and demand 2026-2095

After 2025, CCS costs change due to learning by doing and economies of scale in manufacturing. Changes in the demand for CCS affect manufacturing scale, which can bring down costs if scale increases. Accumulated experience in capturing CO_2 reduces energy penalty and O&M costs. Transportation and storage costs decrease due to technological improvement but increase due to depletion of reservoir capacity (Middleton and Bielicki 2009), thus we model them as constant through time.

2.1.1 Demand curves

We use the GCAM model to estimate the demand for electricity from coal CCS plants between 2025 and 2095 under a variety of assumptions on CCS costs, carbon prices ($Cprice_t$), and spillover among CCS technologies (JGCRI 2013). The total estimated demand D_t depends on the price of the lowest-price CCS technology, $CCScost_{t-5}$, as well as subsidies.

$$D_t = f\left(CCScost_{t-5}, Subsidy_t, Cprice_t, spillover, t\right) \tag{1}$$

To model the competition among the CCS technologies, and acknowledging that they are imperfect substitutes, we use a logistic curve approach (McFadden 1974). The demand $D_{t,s}$ for technology s at time t is a fraction of the total demand for CCS:

$$D_{t,s} = D_t \frac{w_s \cdot CCScost^r_{s,t}}{\sum_s w_s \cdot CCScost^r_{s,t}} \tag{2}$$

where w_s is the base share weight for each technology, $CCScost_{s,t}$ is the levelized cost of each technology, and r is an exponent that determines how sensitive demand is to price.

The ESM includes GCAM assumptions about the price and deployment of other energy technologies. The availability of bioenergy with CCS (BECCS) is other particular importance. Our base results assume that it is unavailable; we discuss the impact of this assumption at the end of the paper and include results in the ESM.

Decisions to build CCS plants are made five years before they come on-line in response to expected future demand at start-up. As in Nemet and Baker (2009), we assume that decision-makers are myopic about technological change and thus, demand (D_t) in eq. 1 is determined by $CCScost_{t-5}$. D_t, in turn, determines the number of CCS *plants* needed in period t. If the number of plants is greater than the existing stock of plants, then new plants (*nplants*) are constructed to make up the difference. The experience and scale effects based on $nplants_t$ reduce $CCScost_t$.

2.1.2 Experience effects

We assume that for each technology, s, Levelized O&M costs ($LAC_{OM(t)}$) and Energy Penalty (EP_t) will reduce with experience. Following work that shows it takes time to assimilate knowledge gained through experience into production processes, we introduce a 1-year lag (Argote and Epple 1990). Thus these calculations require more precision than our general approach of 5-year time steps.

$$LAC_{OM_{t,s}} = LAC_{OM(t-5),s} \left(\frac{CumCO2_{t-1,s}}{CumCO2_{t-6,s}} \right)^{b_{OM}} \tag{3}$$

$$EP_{t,s} = EP_{t-5,s} \left(\frac{CumCO2_{t-1,s}}{CumCO2_{t-6,s}} \right)^{b_{EP}} \tag{4}$$

$$CumCO2_{t,s,0} = CumCO2_{t-5,s,0} + 5 \cdot aCO2stk_{t-5,s} \left(plants_{t-5,s} + nplants_{t,s} \right) \tag{5}$$

$$CumCO2_{t,s} = CumCO2_{t,s,0} + spillover * \sum_{j \neq s} CumCO2_{t,j,0} \tag{6}$$

$$nplants_{t,s} = (plants_{t,s} - plants_{t-5,s}) - moth_{t-5,s} + ret_{t,s} \tag{7}$$

$$b_i = \frac{\ln(1 - LR_i)}{\ln(2)} \tag{8}$$

We proxy experience through the cumulative stock of CO2 captured ($CumCO2_t$). This is equal to the cumulative stock in the previous period plus the average CO2 produced per plant over 5 years ($5 \cdot aCO2stk_{t-5}$) multiplied by the sum of existing and new plants. New plants ($nplants$) is equal to the change in plants needed (first term in eq 7) minus mothballed plants plus plants built to replace retired plants. Since CCS plants last on average 40 years ($life$=40), a number of plants may need to be retired each year starting in 2055 (2015+40). Retirements in the previous 5 years (ret_t) equal the number of plants constructed in the 5 years prior to year, $t - life$. If, after accounting for retirements, the total number of plants needed to meet demand for CCS (D) declines between $t-5$ and t, a number of plants ($moth_t$) are taken out of operation and 'mothballed.' Mothballed plants are available to come back on line in future periods. Because their capital costs are sunk, they are restarted before new plants are built. The presence of knowledge spillovers indicates that technologies can benefit from the experience of other technologies (Nemet 2012a). In our construction of experience stocks for each CCS technology, we assume that each technology receives 50% ($spillover = 0.5$) of the experience generated by other technologies ($j \neq s$) in each period. We include the range 0–100% spillovers in our sensitivity analysis. Each part of the process ($i = OM, EP$) is assigned a learning rate LR_i, using evidence from analogous processes (Baker et al 2012), and an experience factor b_i is calculated for each using eq. 8.

2.1.3 Returns to Scale

Increases in demand for CCS lead to increases in manufacturing capacity for the individual components—gasifiers, air separation units, etc. Manufactures of these components take advantage of the resulting opportunities for cost reductions through, for example, spreading fixed costs, investing in automated processes, and developing specialized equipment. We use empirical estimates from other industries about the effects on unit cost (Cap) of increases from manufacturing scale (Remer and Chai 1990; Sinclair et al 2000), and model it as follows:

$$Cap_{t,s} = Cap_{t-5,s} \cdot \max\left[\left(\frac{nplants_{t,s}}{nplants_{t-5,s}}\right)^{a}, 1\right] \tag{9}$$

where a measures returns to scale rather than learning by doing. Note that demand for CCS is not monotonically increasing over 2025–95 (Figure 2), so we add assume no change in costs (value of 1) when demand for new plants contracts.

2.2 Policy Instruments

We assess how three policy instruments affect coal CCS technology. First, a carbon tax (*cprice*) measured in $\$/tCO_2$ is an exogenous feature that affects the amount of demand for CCS in a given year. GCAM and our model assume that the rate of increase for the carbon tax is fixed at 5% per year. Second, public R&D funding affects the energy penalty in 2025. For early stage CCS technologies, R&D also affects the likelihood that the technology will become feasible and available to deploy at scale. We populate these outcomes using probability distributions from Jenni et al (2013). Third, a *subsidy* can be given for every unit of electricity produced using CCS technology. The subsidy begins at time t and extends for 5 years for each qualifying plant. The subsidy also includes a floor CCS cost, below which the subsidy does not apply.

2.3 Calibration and Parameter Values

In the ESM we show the baseline values and ranges or probability distributions for each parameter, many of which are detailed in Nemet et al (2013). We use the results of a survey of learning rates for technologies relevant to carbon capture and sequestration by Baker et al (2012). The median value from these studies, 0.11, is slightly below the value from a survey of a broad set of learning rates in the energy sector (Nemet 2009), suggesting that CCS may improve at a slower rate than smaller scale technologies, which involve many more units and the opportunities for iterative design. In our model, three of the four components of CCS costs (O&M, EP, and CO_2 transportation costs) improve through the accumulation of experience. We assign a 'learning rate' (LR) to each using evidence from analogous processes (Baker et al 2012) and calculate an experience factor b for each using eq. 8. For transportation costs we assume that the factors increasing costs (reservoir depletion and transport distance) are offset by the factors decreasing costs (scale and technological change) and assume zero learning ($b_3 = 1$) and thus constant costs.

3 Results

Our results focus on the way in which policies impact two main outcomes: abatement cost in mid-century ($/t$CO_2$) and cumulative abatement through 2095 (gigatons).

3.1 Base case outcomes post-2025.

Under our base case assumptions (\$25/tCO2 in 2025, low subsidies, and high R&D), we find that the abatement cost for coal CCS falls by nearly half between its initial commercialization in the 2020s and 2095. This central estimate produces a long-term abatement cost for coal CCS of just under \$40/tCO_2, an installed capacity of 1600 GW, and cumulative abatement of close to 300 GT CO2. Almost all of the technology improvement occurs before 2060. Note that because we are simulating 7 competing CCS technologies, each technology improves at a slightly different rate, due to differences in deployment of each and the shares of capital and operating costs for each. One can see the different rates of change in the ESM figure showing time series of the cost for each of the 7 technologies.

Deployment and cost reductions are closely coupled, as explained by equations 3, 4, and 9. Essentially deployment in period t affects technological change in period $t+5$. Figure 2 shows deployment over time. Demand for electricity from coal CCS grows until 2085 and falls thereafter. Construction of new plants increases until 2050; manufacturing scale increases over that same period, which provides opportunities for cost reductions from economies of scale. Those cost reductions end after 2050, since manufacturing scale remains relatively constant from 2050–85. Much of the new construction after 2070 is to replace retiring plants. Near the end of the century hundreds of operating plants are then shutdown as demand for CCS electricity declines in late century. While these dynamics associated with the late-century decline are relatively inconsequential in the base case, they can have large effects under alternative assumptions that lead to a much earlier decline in demand.

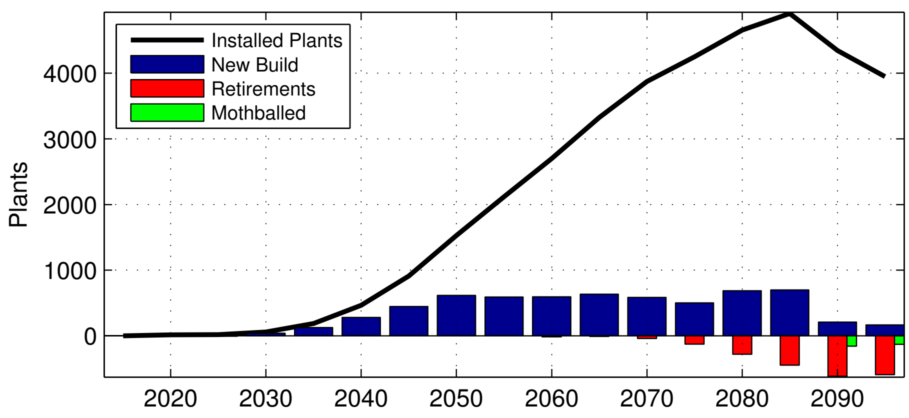

Fig. 2 Deployment of CCS for all technologies, base case assumptions, high R&D.

3.2 Benchmarking

We compare these base case results under high R&D to those of other studies that incorporate technological change into estimates of the future costs of CCS (Hamilton 2009; Rubin et al 2007; Herzog 2011; van den Broek et al 2009; Li et al 2012; Lohwasser and Madlener 2013; Knoope et al 2013). A table In the ESM shows that our initial 2025 costs are toward the lower end of the range of these studies, which seems appropriate given our high R&D scenario and somewhat later commercialization than other studies. Our cost reduction in abatement, 47% is near the high end of the range of previous studies, 9–49%, perhaps because we have been more explicit about technological change and because we include emerging technologies that are not considered available in other studies. Consequently, our long term abatement costs are below those of other studies.

3.3 Sensitivity to alternative assumptions

The above results are merely point estimates based on a single set of assumptions. Next, we incorporate uncertainty in each of the important parameters in the model. We separate these uncertain parameters into 2 types: those that effect costs at the beginning of commercialization, 2025, and those that affect technological change thereafter. For 2025, we include uncertainty in the same parameters assessed in (Nemet et al 2013), energy penalty, capital costs, feasibility, etc. Post-2025, we include distributions of possible values for: learning by doing, returns to scale, knowledge spillovers, and technological heterogeneity.

We assume that both learning by doing (LBD) and returns to scale (RTS) come from a distribution of values found in previous studies of analogous technologies, such as flue-gas desulfurization and selective catalytic reduction of NO_x (Baker et al 2012). We assume that RTS and LBD do not change over time, but that they can differ across technologies. Knowledge spillovers, i.e. experience from one type of CCS can improve another type, range from 0 to 100%. Technological heterogeneity and niche markets also exist and affect the three parameters included in eq. 2. We vary all parameters simultaneously and produce probability distributions over time of costs and abatement.

3.3.1 Sensitivity by technology

First looking at individual technologies, one can see the range of outcomes in box plots for cumulative abatement (Fig. 3) and costs in 2050 (Fig. 4). In each diagram, the box captures the 25th to 75th percentile range for 10,000 iterations. The horizontal line in the box is the median. The dashed lines extend to the 0

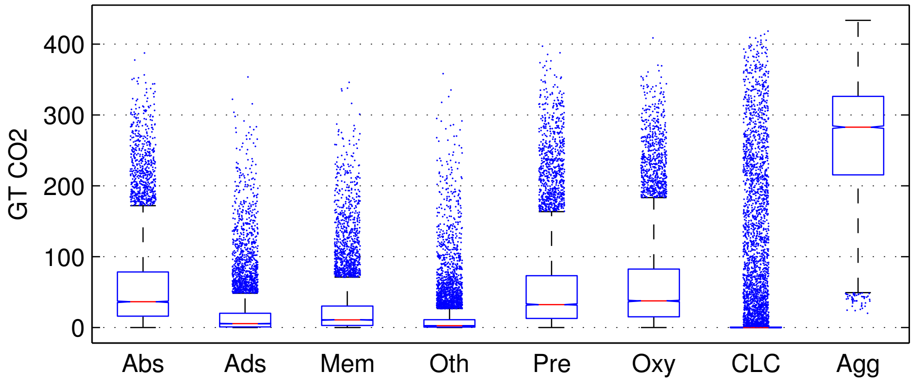

Fig. 3 Distributions of gigatons of CO_2 avoided 2015–2095 by coal CCS.

and 99th percentile. Values above that range are shown as blue dots. In Fig. 4, instances when the technology turns out to be infeasible are also shown as blue dots. In each iteration, aggregate abatement (Agg) is the sum of abatement levels for all technologies; aggregate abatement cost is based on the cost of the lowest cost technology in each iteration. The highly skewed distributions for each technology produce a sum of technology medians that is substantially lower than the aggregate median. The figures show which technologies contribute to the aggregate distribution. For example, one can see in Fig. 3 that abatement is primarily attributable to absorption, pre-combustion, and oxyfuel, even though Fig. 4 shows that chemical looping has the lowest costs when it turns out to be feasible, which is in the minority of iterations.

3.3.2 Sensitivity in aggregate

We assess the same monte carlo analysis over time, focusing on outcomes aggregating all seven technologies. In Fig. 5 the range of outcomes is indicated by the shades of blue (extremes) to white (median), with the solid black line as the median

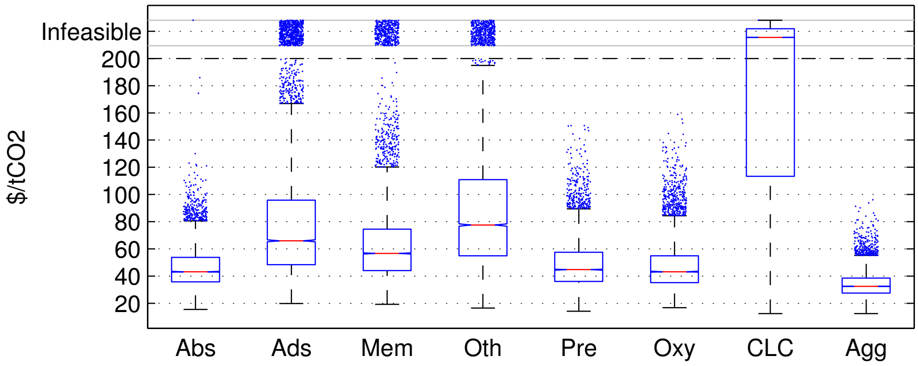

Fig. 4 Distributions of cost of avoided CO_2 from coal CCS in 2050.

value in each time period over 10,000 iterations. Dotted lines indicate the 10th and 90th percentiles. As can be seen in Fig. 3 cumulative CO_2 avoided spans a wide range. The dashed line shows median under the low R&D scenario; it shows the small difference between R&D scenarios relative to the dispersion from all sources of variation. Generally, most abatement occurs after 2060. Much of the dispersion is due to the onset of deployment, which ranges (10–90th) from 2025 to 2065. The ESM provides similar figures for abatement cost and numbers of operating plants. Note that we assume no spillover of technical change from coal CCS to BECCS; we discuss the implications below.

In addition, we check the sensitivity of the results to assumptions about the availability of other low-carbon technologies. We do this by running GCAM using other assumptions and using the resulting alternative demand curves as inputs for our model. In the long-term, which we assess here, the availability of BECCS is a crucial assumption (Edmonds et al 2013; Luderer et al 2013). Our base case assumes that BECCS is unavailable, e.g. due to stringent land use constraints. Indeed, our results show that the availability of BECCS reduces coal CCS deployment considerably: demand for coal CCS peaks 20 years earlier; new construction

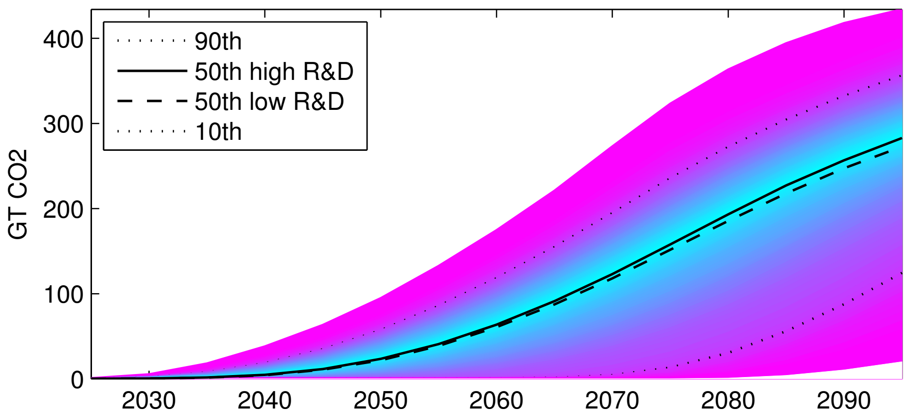

Fig. 5 Time series distributions of gigatons of CO_2 avoided 2015–2095 by coal CCS.

declines after 2050; and cumulative abatement is only half the amount without BECCS. Cost reductions are much less affected since they predominantly occur before 2050 in any case. The ESM provides detail on comparisons of our results with and without BECCS.

4 Effects of policy on abatement and abatement cost

Using the full range of assumptions above, we assess the effects of the three government interventions described in section 2.2: R&D, subsidies and carbon prices. We first look at the effects of the 3 policies—carbon prices, R&D, and subsidies—individually. As in the previous section we iteratively allow each parameter to bay over its entire range and develop probability distributions of outcome metrics over policy values. Carbon pricing varies based on an initial value for 2020 of \$0–75/tCO_2. Thereafter it increases at 5%/year to be consistent with GCAM. R&D policy takes one of two values: business as usual and a high R&D scenario, which is about 5 times current levels. In addition, in cases in which the carbon prices reaches $100/tCO_2$ by 2040, the induced private R&D scenario is triggered (S2 in the ESM). Subsidies are calculated based on four parameters: an initial value for 2025 ($0–100/MWh), the rate at which the subsidy declines (1–30%), a CCS cost floor below which the subsidy no longer applies ($10–50/MWh), and the year the subsidy begins (2025–2080).

The ESM provides figures that compare these policy assumptions to the outcome metrics of interest: cumulative abatement and abatement costs. Deployment is increasing in carbon prices, but with diminishing returns. Median cumulative abatement over the century nearly triples as carbon prices rise from the low single digits to about $70/tCO_2$ (using prices in 2040 as an indicator). However, there is no additional abatement as prices rise above that level; other low-carbon technologies become competitive and the 10% of CO2 not captured with CCS becomes a substantial part of the costs of CCS. Cost reductions show a similar pattern, but with an even lower threshold for diminishing returns to carbon prices, $<$ $50 in 2040. The ESM figures shows that differences in outcomes across policies are small relative to those created by input values.

Subsidies have a more nuanced set of effects. Only post-2040 subsidies increase deployment. Early subsidies (2025-40) shift deployment earlier but have no long-term effect on abatement. This latter result is in contrast to other studies that show that early subsidies can increase long term demand and abatement by accelerating the process of technological change (Nemet and Baker 2009; Nemet and Brandt 2012). The ESM provides detail on the reasons we do not see the same result in this study. Essentially, post-2040 subsidies expand scale at opportune times so that economies of scale are enhanced. As can be seen in Fig. 6, early subsidies merely shift some production earlier so that economies of scale are increased in 2030, but

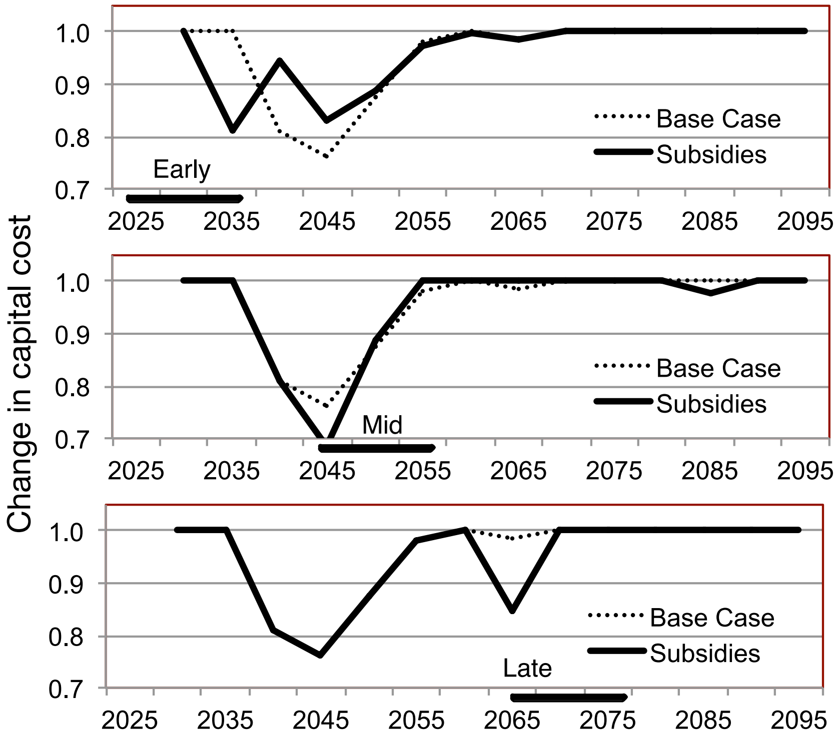

Fig. 6 Effects of subsidy timing on technological change, 2025–95.

are reduced in 2040 and 2045. Because construction of new plants is much higher in the 2040s than it is in the 2030s, the overall effect is an adverse one. Moreover, the elasticity of demand for CCS appears to be lower than that of the technologies assessed in those other studies. At least for capital cost, there is a social benefit to concentrating production in short periods to maximize economies of scale. Because their technological change is based on an accumulating knowledge stock, the other cost components—energy penalty and O&M—improve monotonically. But since they account for a smaller part of costs, the capital cost effect dominates.

Public R&D has only a small effect on deployment and cost reductions. A similarly minor effect is found in earlier work using the same elicitations (Jenni et al 2013; Nemet et al 2013) and is primarily attributable to experts' judgements that R&D would facilitate only incremental improvements in energy penalty and feasibility. We even note some instances in which R&D is associated with slightly worse long-term outcomes. This outcome only occurs under special conditions, and is due to the timing of scale economies described above; this effect is small relative to that of subsidies.

5 Discussion

We found a wide range of future abatement and abatement costs for coal CCS when the full range of uncertainty on input parameters is taken into account. Our central estimates are within the range of those in other studies of coal CCS. They are at the low end for abatement costs, the high end for cost reductions, and the high end for deployment. Our range encompasses the range of estimates in other studies. The research design here is more explicit about the process of technological change and generally more bottom-up about the components of cost than comparable existing studies. Our results are sensitive to the shape of the demand curves, especially how demand for CCS electricity changes with carbon prices. They are also sensitive to what other technologies compete with CCS to provide low-carbon electricity. The availability of BECCS has a particularly large (negative) effect on demand for coal CCS.

From a policy perspective, we found that the results are more sensitive to input assumptions, such as capital costs and returns to scale, than they are to various combinations of policies—even when varying policy parameters over a wider range than is likely politically feasible. Among policies, carbon prices have the strongest effects; they affect deployment of coal CCS, and consequently abatement costs via technological change. However, above a certain level, carbon prices do not increase demand for coal CCS, as the non-captured emissions become expensive and other low-carbon technologies become competitive. The effects of R&D, which we elicited from experts, were quite modest. R&D reduces energy penalty and increases the feasibility of early stage capture technologies like chemical looping. But those effects are essentially lost in the noise of possible outcomes for parameters such as feasibility, capital costs, and scale. The multiple elements of subsidy design and their interaction with CCS manufacturing scale complicate optimal design of subsidies. Subsidies seem most effective when timed to coincide with expansion of the manufacturing capability, such that subsidies enhance economies of scale. But that timing also makes them expensive, as they are subsidizing more than just early-stage demand. In our model subsidies in the early years shift deployment earlier but have little effect on long-term abatement or cost reductions. They do seem helpful in avoiding the worst outcomes (low deployment and high costs).

The large uncertainties in input parameters allow only general guidance about the magnitudes of policy effects. The primary normative implications of this study are to point to areas of missing information. These results, in combination with our dozens of hours of interviews with CCS experts, highlight 4 parameters for which poor information seriously impedes the decisions policymakers face.

Capital costs: Our extensive review of the literature revealed a factor of 4 range in near-term estimates for the cost of building CCS plants. While the experts we spoke with were reluctant to provide judgements about capital costs, their responses generated a consensus that public R&D investment was unlikely to have much effect on them. Bottom-up modeling of returns to scale helps characterize cost dynamics, but future costs are sensitive costs at early adoption.

Demonstration Plants: Experts were also generally in agreement that construction of a series of demonstration plants would be more important than public R&D. They consider demonstrations essential for reducing uncertainty in capital costs and improving reliability, such that the risk of operating full scale plants in real commercial environments would be low enough to stimulate early adoption. We currently have little basis for understanding: how many demonstration plants would need to be built; how much knowledge about them could be retained by the firms that build them; and consequently, to what extent firms would be willing to fund them on their own.

Growth constraints on scale: Our results make clear that subsidies have the most favorable effects when they maximize returns to scale in the production of CCS components. A logical conclusion based on the benefits of scale is that it would be more efficient to construct CCS plants in a short period of time rather than steadily at a low level over a longer period. We observed this effect previously in modeling technological change in solar (Nemet and Baker 2009). Our approach does not consider supply-side constraints on growth, e.g. through supply-chain bottlenecks, although the demand curves reflect built-in growth constraints within GCAM. It's not clear however that our approach is biased. Using one of the few data sets used to study growth constraints empirically, Wilson et al (2013) found that IAMs overly constrain growth compared to the historical evidence. Because the gains from scale are substantial, getting the policies right to make the most of them depends on understanding how opportunities for scale economy are limited by real-world constraints.

Spillovers from coal to other CCS: Finally, spillovers among technologies are likely to play an important role in whether polices designed to induce technological change are efficient. Our study simulated spillovers among 7 types of coal CCS technologies; experience in one type of CCS provided opportunities for improvements in others. But we have very little basis for anticipating what the level of spillover is likely to be. Even more importantly, given the strong negative relationship we see between the availability of BECCS and the adoption of coal CCS, understanding whether R&D on coal CCS will ultimately prove useful for BECCS is crucial. For that reason we likely underestimate the effects of R&D. The scale of the potential abatement benefits we have found here suggests that the stakes to society of designing effective technology policy for CCS are large.

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Electronic supplementary material for: *Characterizing the effects of policy instruments on the future costs of carbon capture for coal power plants*

Gregory F. Nemet   Erin Baker   Bob Barron
Samuel Harms

May 2014

This electronic supplementary material (ESM) document provides further details on the methodology and values used in this study. It also provides additional results and sensitivity analyses.

Contents

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List of Tables

A Policy scenarios and technology definitions

This model assesses initial conditions (2025) under 3 policy scenarios. It assesses 7 types of capture technologies.

A.1 Elicitations under 3 policy scenarios

Our elicited values for energy penalty and feasibility were conditional on three R&D scenarios (Nemet et al., 2013):

Scenario 1 (S1): No further US government funded research and development (R&D) in CCS (i.e., zero public investments in future years), current worldwide carbon price (∼\$5/tCO_2) is unchanged;

Scenario 2 (S2): No further US government funded R&D in CCS, worldwide carbon price equivalent to \$100/tCO_2 starting in 2015 and continuing indefinitely;

Scenario 3 (S3): "High" US government investment in R&D (an annual investment level about five times the 2005 investment was defined for each technology) from 2015 through 2025; current worldwide carbon prices are unchanged.

A.2 Technology categories

As in Jenni et al. (2013), we divided carbon capture into 7 areas of technology, which were sufficiently distinct to elicit clear responses and aggregated enough that multiple experts were available for each technology.

1. **Absorption:** post-combustion using absorption via solvents, including MEA, ammonia, and novel solvents
2. **Adsorption:** post-combustion using adsorption, including solid sorbents and metal organic frameworks
3. **Membranes:** post-combustion using membranes, including ionic liquids
4. **Other PC:** post-combustion using other approaches, including enzymes and cryogenics
5. **Pre-combustion capture:** typically with integrated gasification combined cycle (IGCC)
6. **Oxyfuel:** alternative combustion using pure oxygen rather than air
7. **Chemical looping combustion:** use of metals to transport oxygen

Figure S1 provides a general overview of this sequence of calculations and how policy instruments affect them. These calculations are performed separately for each of the 7 capture technologies.

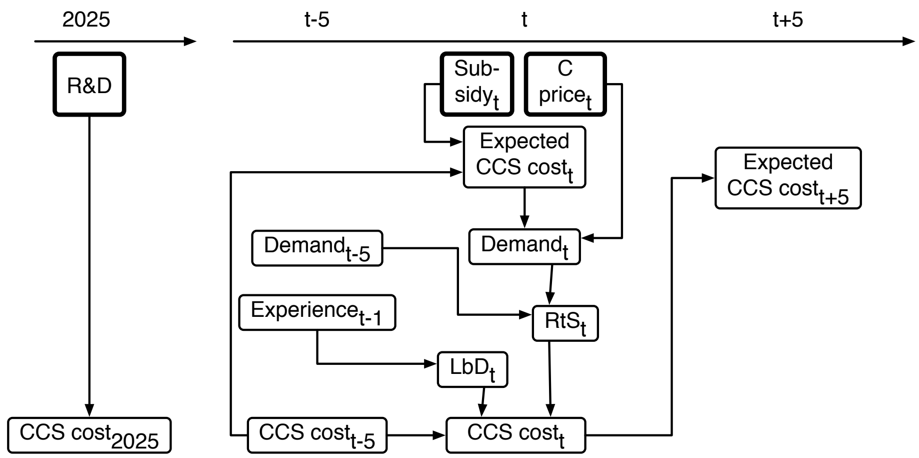

Figure S1: Schematic of calculations of technological change.

B Calculations for early deployment, 2015–25

B.1 Demonstration plants, 2015–20

We assume that 10 demonstration plants are built between 2015 and 2020. Fitting with the notion that at first plants become worse before they get better (Rubin et al., 2007), we assume these plants perform inferiorly to subsequent plants on several metrics; they have lower CO_2 removal efficiency (80%), higher energy penalty (30%), and lower capacity factor (60%).

B.2 Costs in 2025

CCS technology becomes proven in 2020 and thereafter, CCS plants are built and operated in response to demand for CCS electricity in each period. We calculate additional levelized cost of electricity ($/MWh) and the cost of avoided CO2 emissions ($/tCO2) of CCS plants in 2025 using the values and calculations described in Nemet et al. (2013). We summarize those calculations as follows:

Levelized Cost of Electricity (LCOE): To calculate the additional LCOE in $/MWh from CCS, we calculate levelized annual cost (LAC) of CCS ($/year) and divide by the annual energy produced (AEP) by a reference plant (MWh/year) with CCS. We assume that demand grows linearly between 5-year periods and thus calculate the number of plants installed (*plants*), the electricity produced (*elec*), and the amount of CO_2 avoided (*co2a*) for each year 2021-2025.

For more detail on the costs calculations see Nemet et al. (2013), which we use for all calculations through 2025, as well as for the general approach thereafter. As described in that paper, the energy penalty (EP) of plants in 2025 is determined by expert elicitations conducted by Jenni et al. (2013). These elicited EPs are conditional on the 3 above policy scenarios involving carbon

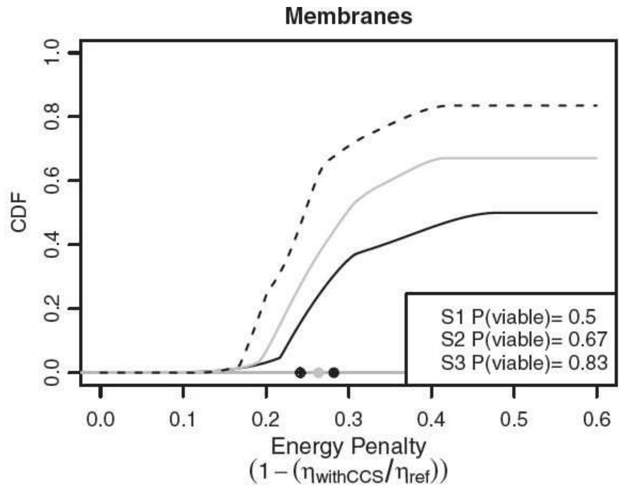

Figure S2: Impact of carbon pricing (S2) or increased research funding (S3) on the aggregated EP distribution of post-combustion with membranes.

pricing and public R&D investment. These policy instruments determine 2025 energy penalty, which in turn affects the cost of CCS in 2025.

Summarizing the main results from Jenni et al. (2013): R&D increased energy penalty by 6–14% vs. reference case and Carbon prices increased energy penalty by 1–10% vs. reference case. Fig. S2 shows an example of the output aggregated across experts for one technology, post-combustion CCS using membranes. Summarizing the main results from Nemet et al. (2013), Fig. S3 shows the full distribution of abatement cost outcomes in 2025 including variation in all parameters.

B.3 Demand in 2025

Construction and operation of CCS plants is based on demand for electricity from CCS plants. As described below, we construct demand curves for CCS electricity using the Global Change Assessment Model (GCAM) (JGCRI, 2013). We apply the calculated costs of CCS (LEC_{CCS}) to these demand curves to determine a level of demand in exajoules for CCS electricity in 2025. Demand for CCS in our model depends on its cost and other factors, as described below. We calculate total demand for CCS (in EJ) and then use capacity factors to convert annual EJ to MW of needed capacity to produce that energy. Taking the total MW needed and the average plant capacity of the stock of CCS plants in that year, we find the number of installed plants required to meet demand in 2025. We assume that demand grows linearly between 5-year periods and thus calculate the number of plants installed ($plants$), the electricity produced ($elec$), and the amount of CO_2 avoided ($co2a$) for each year 2021-2025.

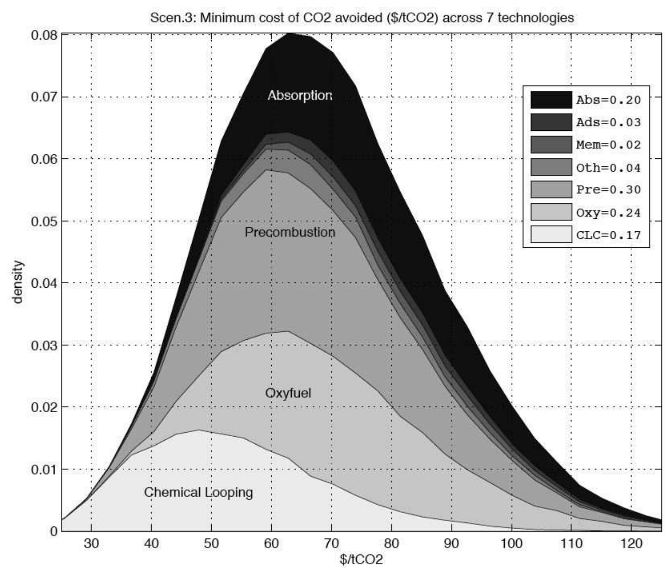

Figure S3: PDF of abatement costs in 2025.

C Calculations of technological change

Table S1 describes the variables referred to in the main text and in this ESM.

C.1 Production-related cost reductions

Learning by doing has most commonly been represented as a power function, for its simplicity and good fit to observations. Measures of fit for energy technologies are often well above 0.90 (McDonald and Schrattenholzer, 2001). Studies of learning rates for O&M costs have been calculated for an array of similar technologies (Taylor et al., 2005; Nemet, 2007). Estimates of O&M learning rates for CCS in particular also exist (Rubin et al., 2007; Yeh and Rubin, 2007; van den Broek et al., 2009; Li et al., 2012). Each component can improve from production related improvements. Table S2 summarizes our approach. Separately, we assumed that non-energy process cost improvements would occur (based on lit review figures) between 2015–25, if demonstration plants were built. If no demonstration plants built, then process costs in 2025 = process costs in 2015. All of our calculations in the main text and in the ESM assume demonstration plants are built.

C.2 Returns to scale

We use estimates of cost reductions that result from up-scaling in the chemical and related industries, which probably includes the largest set of empirical

Table S1: Variable definitions.

Name	Description
D	Demand for coal CCS (EJ)
EP	Energy penalty (%)
$CCScost$	Additional levelized cost of CCS ($/MWh)
$plants$	Plants required to meet demand
$nplants$	New plants built
$elec$	Electricity produced
$co2a$	CO_2 avoided (tCO2)
$life$	Lifetime of CCS plants (life)
ret	Existing plants retired
$moth$	Existing plants not operating
$manf$	Manufacturing capacity (plants/year)
$aepstk$	Annual energy produced (MWh/year) for existing plants
$Epstk$	Energy penalty of existing plants
$CumCO2$	Cumulative CO2 avoided (tCO2)
LR	Learning rate
b	Learning exponent
a	Scaling exponent
s	CCS technologies 1–7
α	Portion of D met by least cost technology
$subsidy$	($/MWh)
$cprice$	carbon price ($/tCO2)
w	base share weight for each technology
r	exponent determining sensitivity of demand to price

Table S2: Components of Base Case Manufacturing Cost and Relationship Between Unit Cost and Output.

Cost component	T1 % of LEC_{2025}	Mechanism for $\triangle$ cost	System boundary	b value
Energy use	0.2	LbD	Firm	-0.20
Process costs	0.10	LbD	Firm	-0.20
Transmission and storage	0.15	LbD, depletion	Industry	0.00
Capital cost	0.55	Manf. scale	Facility	-0.17

estimates on scale (Sinclair et al., 2000). Moreover, the processes in the chemical industry are rather similar to those in a CCS plant. We use estimates of scaling parameters from 570 manufacturing processes surveyed by (Remer and Chai, 1990). These include chemical processes, oil refineries, power plants, pollution controls. For the 570 scaling factors, we calculated the following descriptive statistics: mean= 0.68; median= 0.68; standard deviation= 0.13; minimum= 0.23; maximum= 1.07. We use these statistics to propagate distributions through our model.

C.3 Experience stocks

We construct stocks of cumulative MWh produced ($ExpMWh$) using:

$$ExpMWh_t = aepstk_{t-5}\left(plants_{t-5} + \left(\sum_{t-4}^{t-1} nplants\right)\right) \tag{1}$$

Similarly, we construct stocks for $ExpCO2$. We calculate tCO_2 in year $t-1$:

$$ExpCO2_t = ExpMWh_{t-1}co2a_{t-5} \tag{2}$$

By averaging the total tCO_2 in $(t-1)$ and $(t-6)$ and multiplying by 5, we calculate the tCO_2 avoided in that 5-year period ($co2a$). This allows us to track cumulative CO_2 avoided since the beginning of the industry ($cumCO2$). While EP improves for new plants as shown below, the industry-wide EP ($EPstk_t$) takes into account the number of plants built in each time period and the EP at the time each was built. Generally $EPstk_t$ is higher than that of new plants, EP_t. We use this $EPstk$ to calculate the total MWh produced and tCO_2 captured for our experience stocks, which are described in the main text.

D Calculations of demand for CCS

This section expands on the explanation of CCS demand in section 2 of the main text.

D.1 Using GCAM for demand

We use the Global Change Assessment Model (GCAM) model to calculate demand for CCS electricity (JGCRI, 2013). GCAM models CCS as an add-on to the base fossil fuel technology. The base plant, the CCS plant, and the storage facilities are each characterized by their own independent parameters and variables. Parameters are specified exogenously and can be adjusted; variables are endogenous and must be retrieved after the model runs. We define the cost of CCS as the final price of electricity produced with CCS, net of all production transport and storage costs. The cost of CCS in GCAM is given by:

$$p_{CCS,t} = \frac{1}{\eta_{b,t}}\left(K_{b,t} + C_{f,t}\eta_{c,t}\left(\frac{\tau_t}{\eta_{c,t}} - \tau_t + p_{f,t} + K_{c,t} + E_{c,t}p_{e,t} + p_{s,t}\right)\right) \quad (3)$$

where: C_f = Carbon content of fuel, E_c = CCS energy requirement, K_b = Capital cost of the base plant, K_c = Capital cost of the CCS plant, η_b = Conversion (thermal) efficiency of base plant, η_c = Capture efficiency of CCS plant (% carbon captured), p_f = Market price of fuel, p_e = Market price of electricity, p_s = Price of storage, τ = Carbon tax, and t indexes time.

Based on these costs, GCAM generates demand data (in EJ) for CCS technology. Iterating across CCS costs, carbon prices, etc., yields matrices of model outputs, which we use to construct demand curves. Demand curves are downward sloping and generally, although with exceptions, shifted higher at higher carbon prices. Fig. S4 provides an example. Our demand data from GCAM provide 4 different demand curves based on discrete levels of carbon tax ($15, $30, $45, $60/t$CO_2$) in 2025 (which rise thereafter at 5%/year), resulting in 4 different levels of demand for CCS (Fig. S5). As an additional example, Fig. S6 shows demand at the 4 carbon prices over time under 2 assumptions on CCS prices (upper and lower panels).

As discussed in the main text, we use a logistic curve approach (McFadden, 1973) to model the competition among the CCS technologies, and acknowledging that they are imperfect substitutes. The demand $D_{t,s}$ for technology s at time t is a fraction of the total demand for CCS:

$$D_{t,s} = D_t \frac{b_s p_s^r}{\sum_s b_s p_s^r} \quad (4)$$

where b_s is the base share weight for each technology, p_s is the levelized cost of each technology, and r is an exponent that determines how sensitive demand is to price. As an example, Fig. S7 shows the allocation of market beginning with the least cost technology, T1 ($22), T2 ($40), T3 ($60), and T4 ($70). Note that T3 does not supply all of the demand it is allocated by α_3 because its costs exceed WTP at that point at which T2 demand is limited by the allocation ($\sim$ 1EJ).

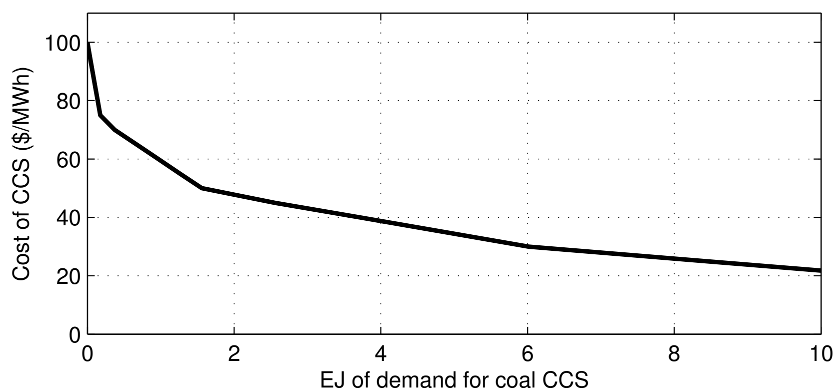

Figure S4: Example demand curve for coal CCS in 2045 at carbon price of $80/tCO$_2$.

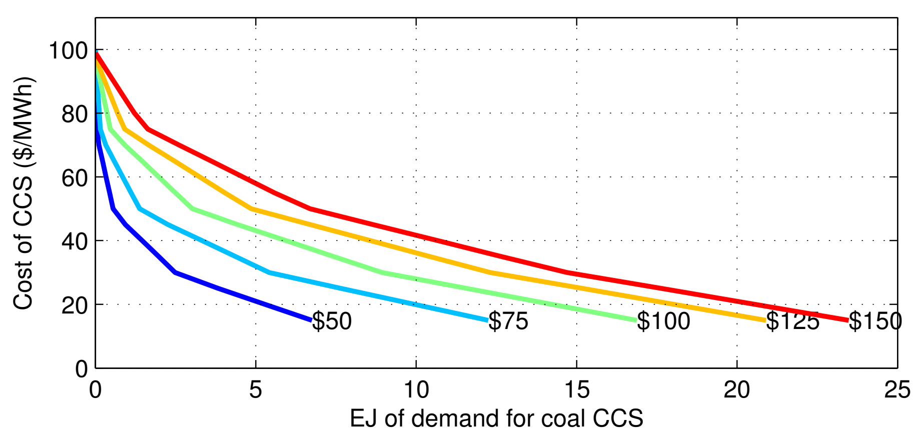

Figure S5: Example demand curve for coal CCS in 2045 at varying carbon prices ($/tCO$_2$).

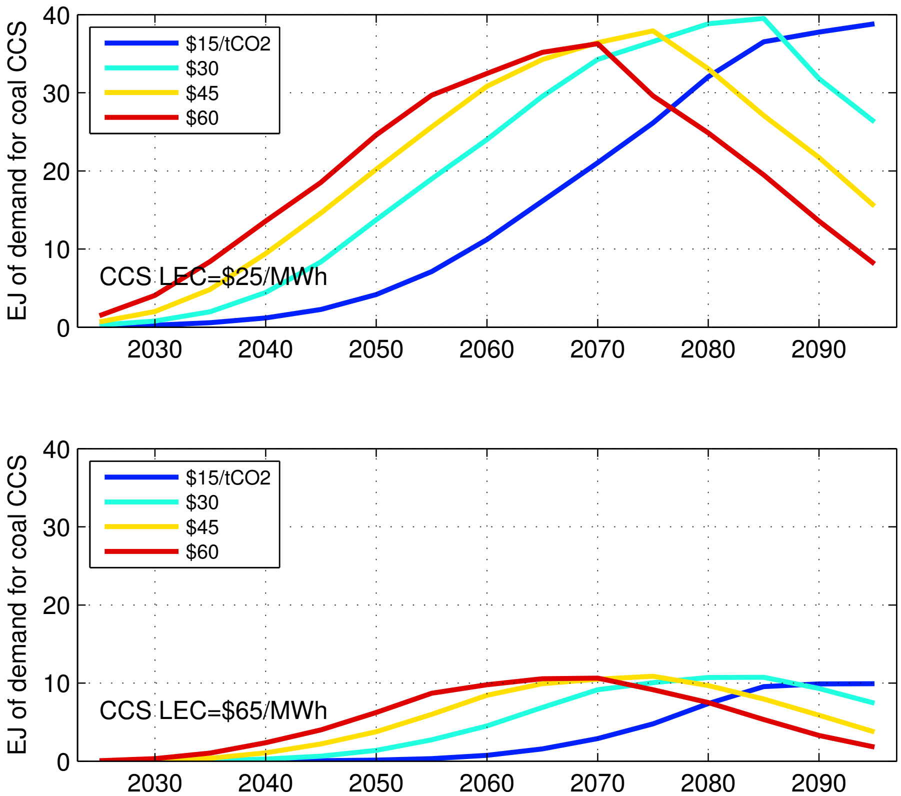

Figure S6: Example demand curves for coal CCS 2025–95 at constant CCS costs and carbon prices ($/t$CO_2$) rising at 5%/year. Legend shows carbon price values in 2025. CCS cost in upper panel is $25/MWh and in lower panel is $65/MWh.

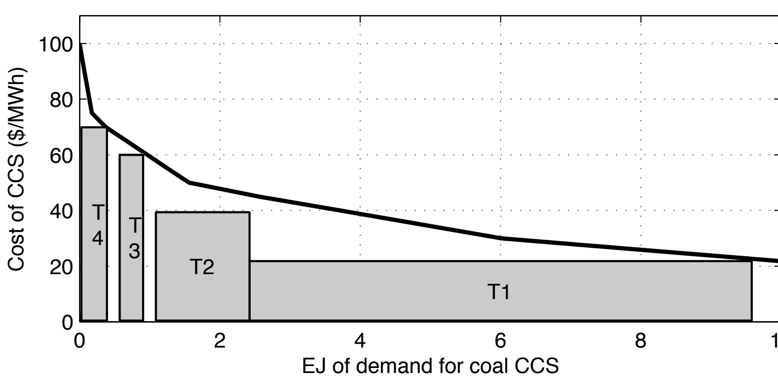

Figure S7: Example of allocation of demand over competing technologies.

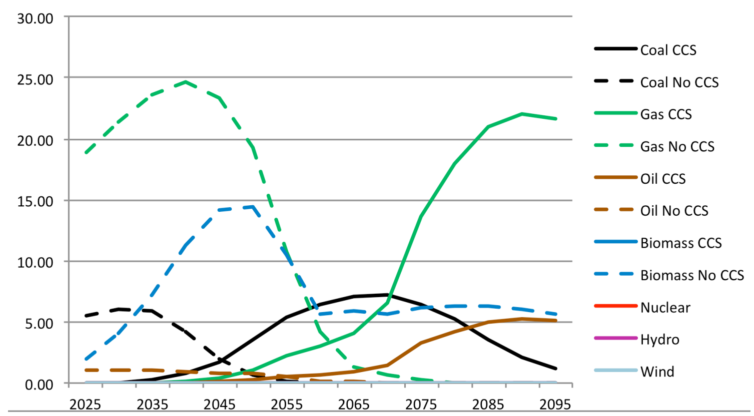

Figure S8: GCAM assumed production (EJ) by each technology 2025–95.

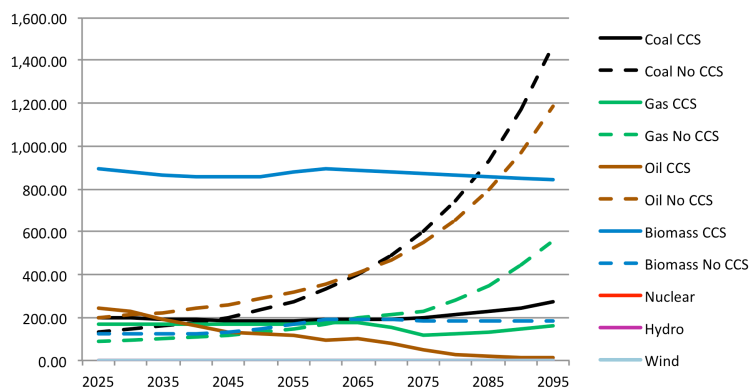

Figure S9: GCAM assumed price (2010 $/MWh) for each technology 2025–95.

D.2 Base technology characteristics in GCAM

Our runs with GCAM include assumptions about the state and future of several technologies that compete to meet demand. The following figures provide a summary of these assumptions. Fig. S8 shows energy production (EJ) by each technology over the century. Fig. S9 shows the prices (2010 $/MWh) for each technology over the century. Fig. S10 focuses on demand for CCS technologies. Note that these represent base technology assumptions in GCAM. The cost of coal CCS deviates from these assumptions according to the calculations for returns to scale and learning by doing described in this model.

D.3 Inter-fuel spillovers in GCAM

Similarly to the way that knowledge in one coal CCS technology spills over to another, knowledge can spillover from one type of CCS power plant to another.

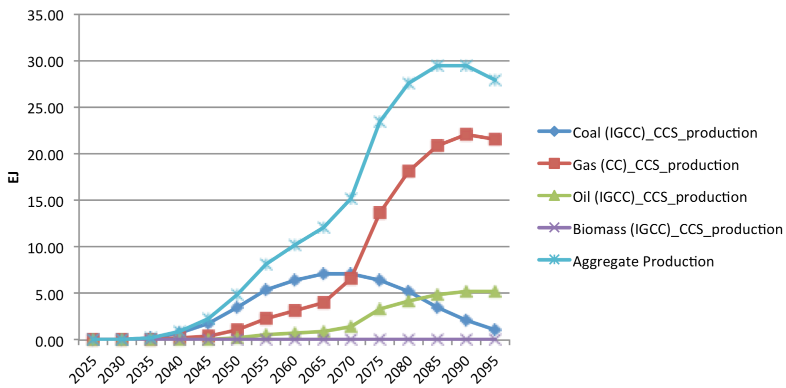

Figure S10: GCAM assumed production (EJ) by each CCS technology 2025–95.

GCAM provides additional demand curves based on "spillover" into different technologies: that is, as CCS improves for coal plants, it may also improve at the same rate for other technologies, such as natural gas, oil, and biomass. The amount of allowable spillover affects the demand for coal CCS. In the model, spillover can be 100%, 50%, or 0%.

D.4 Retirements and mothballing

We assume that the mothballed plants in any given year were built in the period of highest plant construction within one operational lifetime prior to the current period. These plants are excluded from calculations of the EP of the existing fleet and the average capacity of available plants, which affect the number of *plants* needed in a given time period. New plants may also need to be constructed, for one or both of the following reasons: to make up for the CCS production lost to retirements, and to satisfy any increases in demand for CCS over the previous time period.

$$\sum_{t-4}^{t} nplants = (plants_t - plants_{t-5}) - moth_{t-5} + \sum_{t-4}^{t} ret \qquad (5)$$

Construction of plants cannot be negative. If the equation returns a negative number, that number of plants is mothballed. Additionally, if demand increases and new plants are needed, having a stock of mothballed plants reduces the number of plants that need to be built.

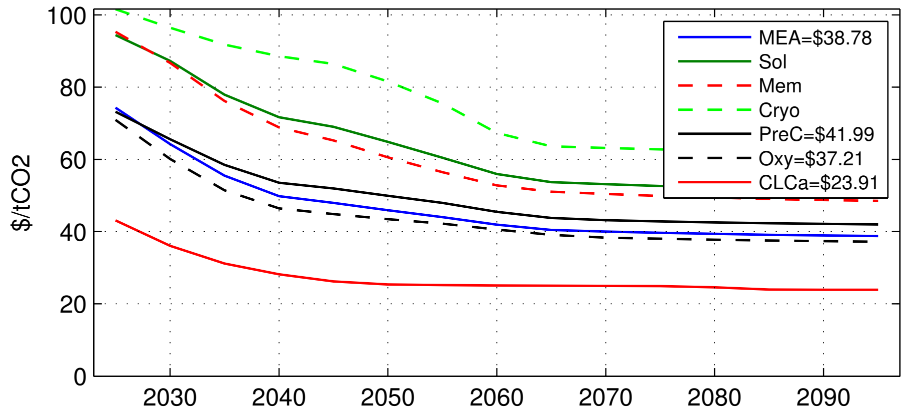

Figure S11: Time series of abatement costs for each technology using median values, with R&D, and conditional on all technologies being feasible.

Source	Starting Year	Technology, if Specified	Starting Costs ($/t$CO_2$)	End costs ($/t$CO_2$)	% Change	Installed Capacity
This paper	2025	Multiple	$74	$39	47%	1650 GW
Herzog (2011)	2010	-	$123	$62	49%	-
Li et al. (2012)	-	IGCC	$103	$61	41%	100 GW
Rubin et al. (2007)	-	Post-combustion	$80	$69	13%	100 GW (each technology)
		IGCC	$69	$58	16%	
		Oxyfuel	$85	$78	9%	
Lohwasser et al. (2013)	-	-	-	-	-	154-217 GW (Europe)
van den Broeck et al. (2009)	2010	PC	$75	$60	21%	1250 GW (combined)
		IGCC	$73	$51	30%	
Knoope et al. (2013)	2010	IGCC	$113	$75	33%	743 GW total (271 from IGCC)
Hamilton (2009)	-	-	-	-	-	Base case: 680 GW

Figure S12: Comparisons of key output measures to other studies of technological change in CCS.

E Base case results and benchmarking

Figure S11 shows the base case results for the costs of each CCS technology over time. In Figure S12, we compare our base case results to those of other studies that incorporate technological change into estimates of the future costs of CCS (Hamilton, 2009; Rubin et al., 2007; Herzog, 2011; van den Broek et al., 2009; Li et al., 2012; Lohwasser and Madlener, 2013; Knoope et al., 2013). One can see that our initial costs are within the existing range of studies, although toward the lower end. Our cost reduction in abatement, 47% is near the high end of the range of previous studies, 9–49%.

F Additional results: sensitivity to input assumptions

To supplement what is included in the main text, we provide additional results to illustrate the effects if changes in input assumptions. We run 10,000 iterations sampling in each instance from the distribution of input assumptions shown in Fig. S13. In Fig. S14 we show the distributions of cumulative abatement over the 21st century for each technology, as well as for aggregate abatement with the 7 capture technologies competing with each other. Fig. S15 provides similar results for CCS abatement costs in mid-century.

We show the same results, with more compact comparison across technologies in the following box plots. Fig. S16 shows cumulative abatement, S17 shows abatement costs in mid-century, and S18 shows the peak number of installed plants for each technology during the century. In each diagram, the box captures the 25th to 75th percentile range for 10,000 iterations. The horizontal line in the box is the median. The dashed lines extend to the 0 and 99th percentile. Values above that range are shown as blue dots.

Next we show these same monte carlo results over time. Figure S19 shows time series for abatement costs including variation in all parameters over 10,000 iterations. Figure S20 shows operating plants across these iterations. Figure S21 a similar analysis for cumulative abatement. This figure is also included in the main text.

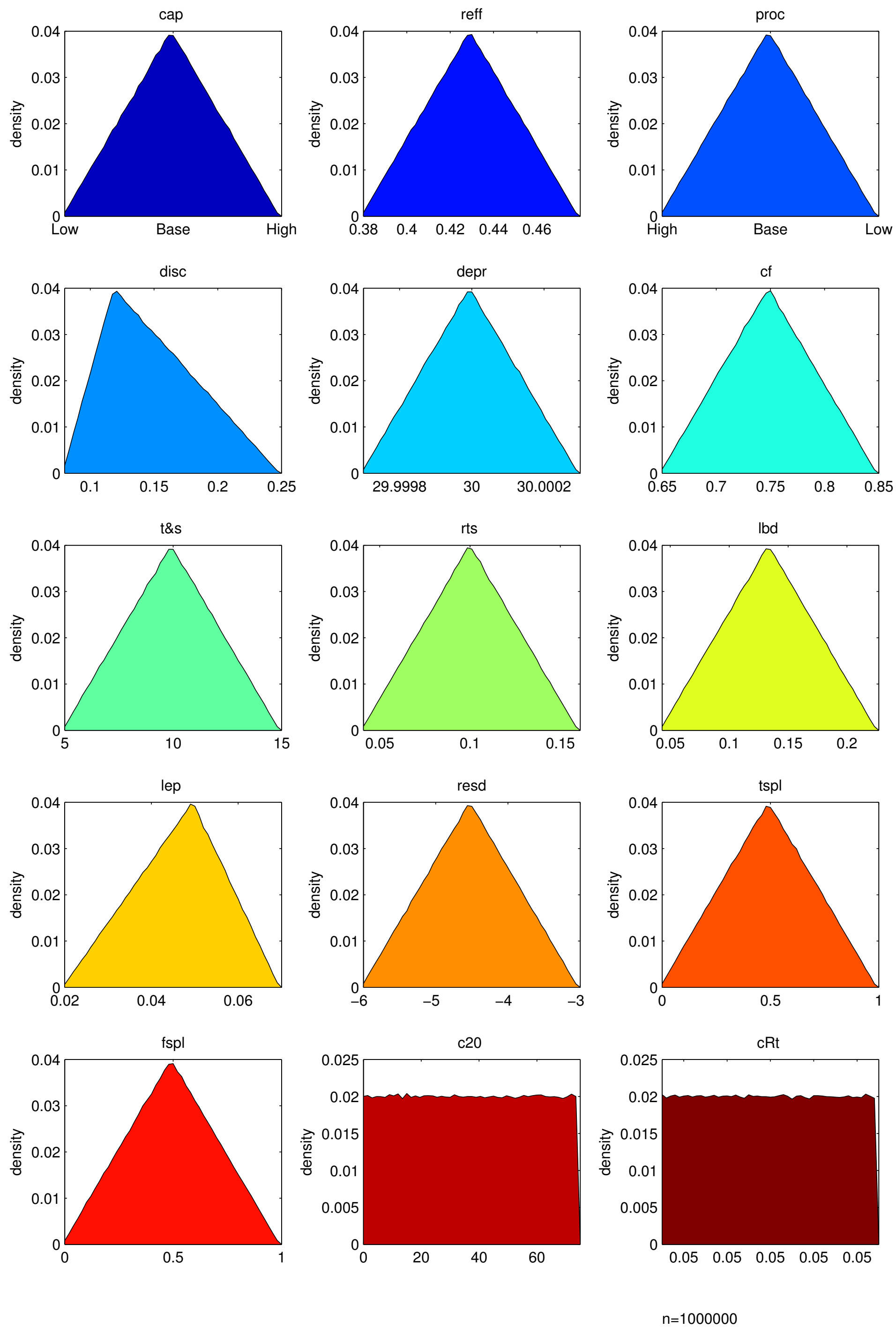

Figure S13: Assumed distributions of parameters included in sensitivity analysis.

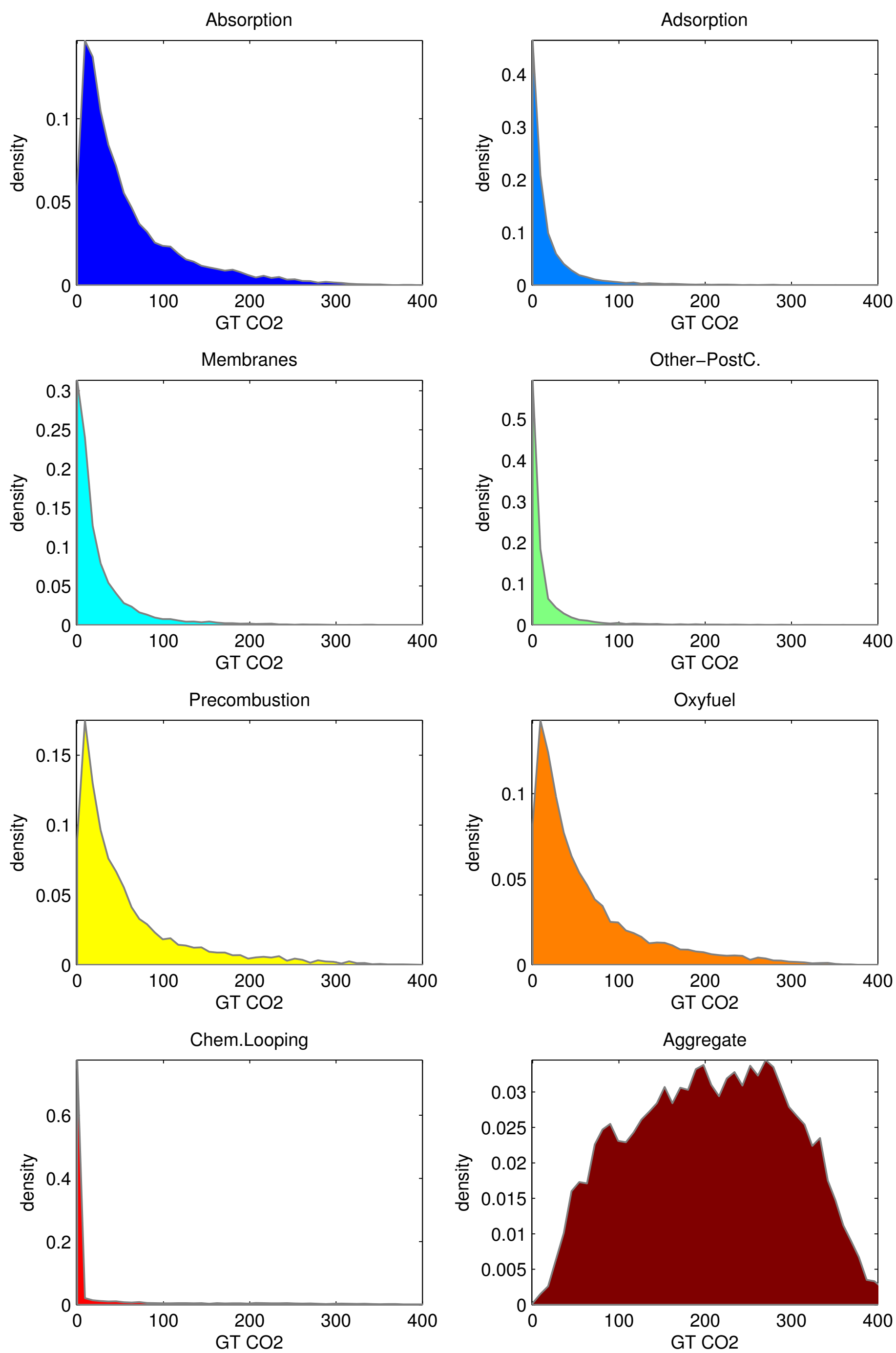

Figure S14: tCO_2 avoided 2015-2095.

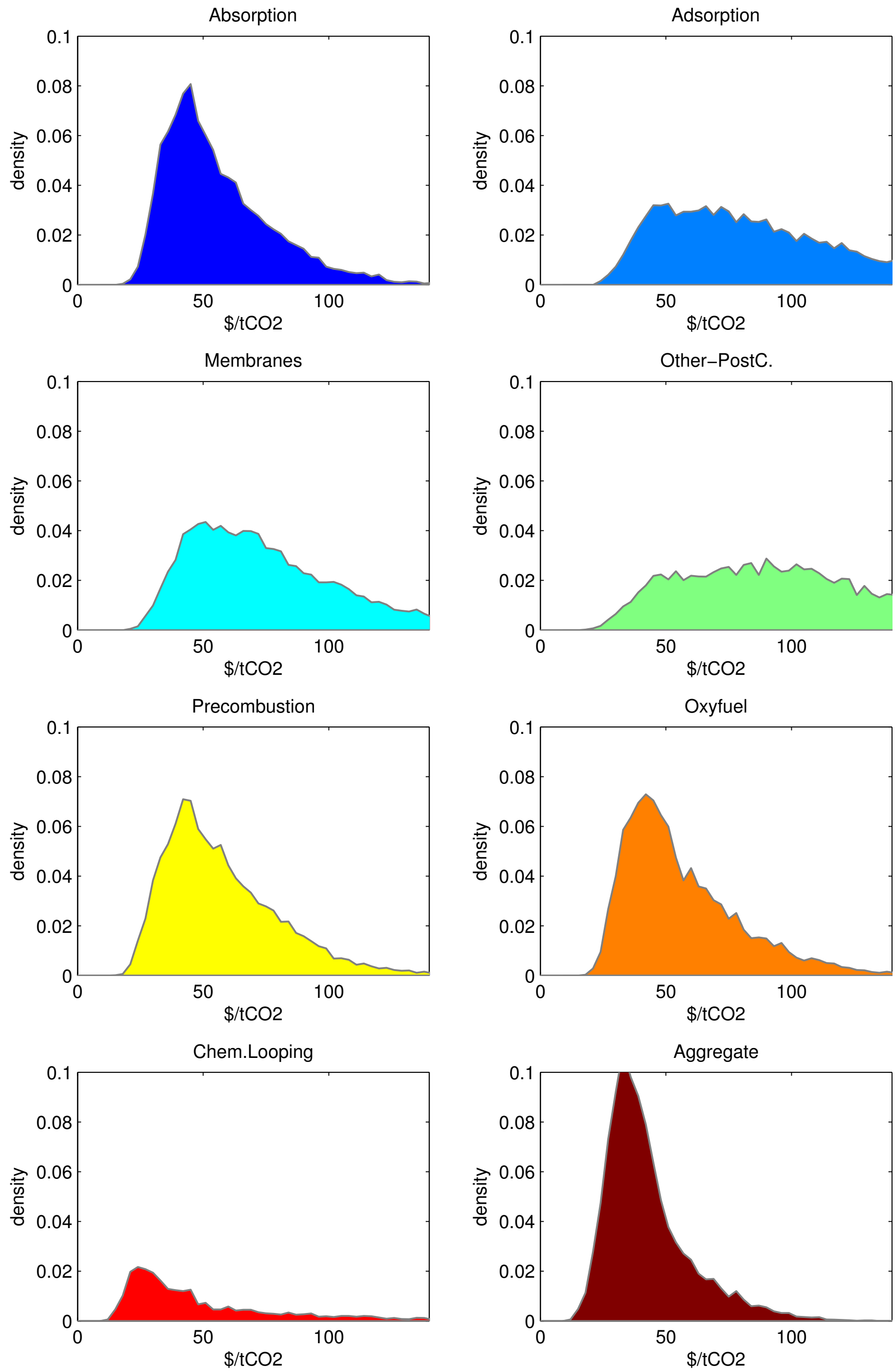

Figure S15: $\$/tCO_2$ avoided 2050.

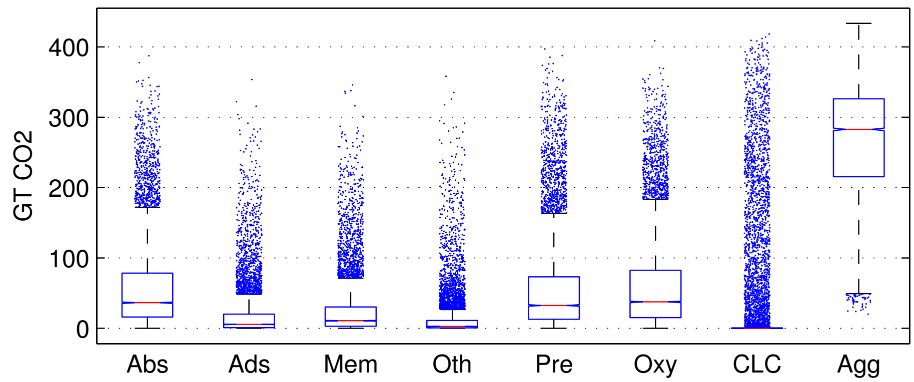

Figure S16: Gigatons of CO_2 avoided 2015–2095.

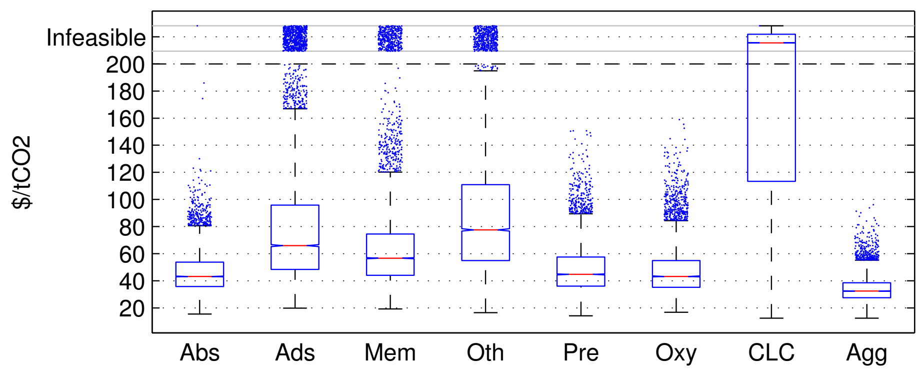

Figure S17: Cost of avoided CO_2 in 2050.

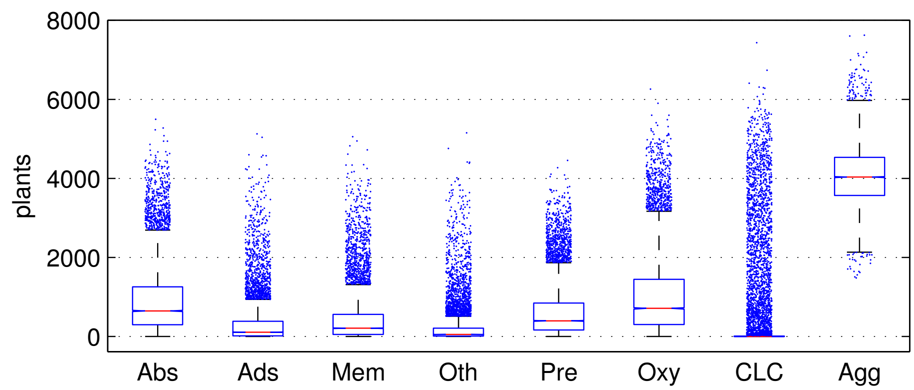

Figure S18: Maximum installed plants 2015–2095.

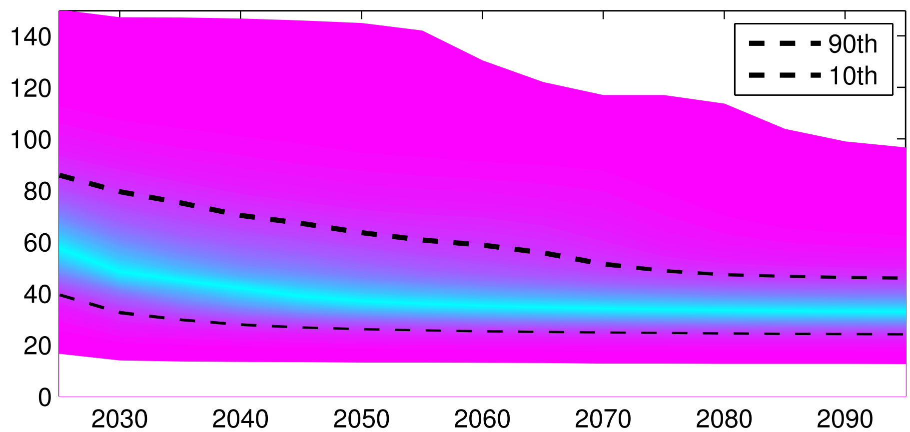

Figure S19: Cost of avoided CO_2 ($/t$CO_2$) 2015–2095 by coal CCS.

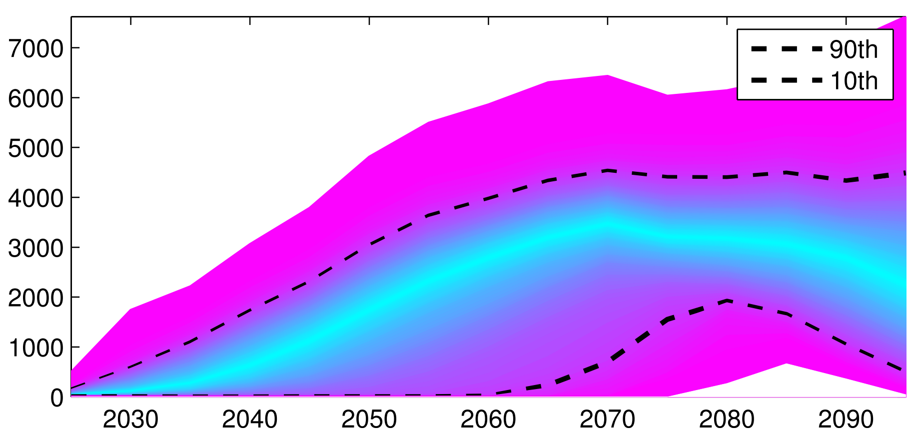

Figure S20: Operating plants 2015–2095 by coal CCS.

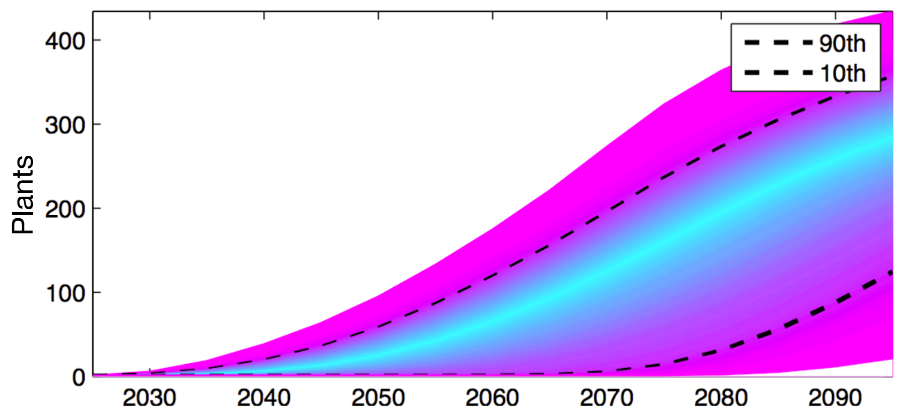

Figure S21: Time series distributions of gigatons of CO_2 avoided 2015–2095 by coal CCS.

G Availability of BECCS

Bioenergy with carbon capture (BECCS) is an important technology to climate change mitigation (Kriegler et al., 2014). It is distinct from CCS for fossil fuels in that it can provide negative emissions. It is one of the few technology options, which can compensate for emissions that overshoot targets in early years. Given that discounting is influential over multi-decadal decisions, being able to postpone abatement until the distant future is attractive. However, there are serious uncertainties involved. In addition to the uncertainties about CCS for fossil fuels, BECCS must address concerns about competition for land use, particularly because its deployment would have to be truly massive to offset emissions from earlier in the century. The issues involved are quite similar to those faced by biofuels for transportation. It is possible that BECCS will be available as a negative emissions option for the second half of the 20th century. It is also possible that its use will be quite minor if land use and other issues prohibit its widespread deployment.

In the main text we assumed that bioenergy with CCS (BECCS) is not available. Here we show results for the case in which BECCS is available. Table 3 compares outcomes whether assuming BECCS is available or not. It includes our base case scenario (No BECCS), an alternative scenario in which BECCS is available, and a second alternative in which neither BECCS nor any other type of bioenergy is available. First, the results show that the biggest difference from the base case is making BECCS available. Removing BECCS has a significant impact on the results, But there is little if any difference between the base case and excluding other types of bioenergy. Allowing BECCS reduces abatement by coal CCS by more than half. Allowing BECCS also limits cost reductions, but to a much lesser extent than it limits abatement. This is because most cost reductions occur in the first half of the century and most BECCS deployment

Table S3: Comparison of outcomes under assumptions about bio-energy: Base case assuming BECCS is unavailable; assuming BECCS is available; and assuming no bio-energy at all.

	Base case No BECCS	BECCS available	No Bio energy
Abatement (GT)	287	134	292
Cost ($/t$CO_2$)			
Post-C	$38.8	$42.0	$38.6
Lowest	$23.9	$25.3	$24.0
Cost reduction 2025–95	49%	45%	49%

occurs in the second half.

As an example of the effect of BECCS, Fig S22 shows deployment without and with bioCSS. One can see that demand for electricity from coal CCS declines steadily after mid-century. This is due to the deployment, and future availability, of BECCS reducing the need for abatement from coal CCS. Note that the figures use different scales on the vertical axis. So peak demand in the top panel (no BECCS) is approximately double that of the with-BECCS scenario.

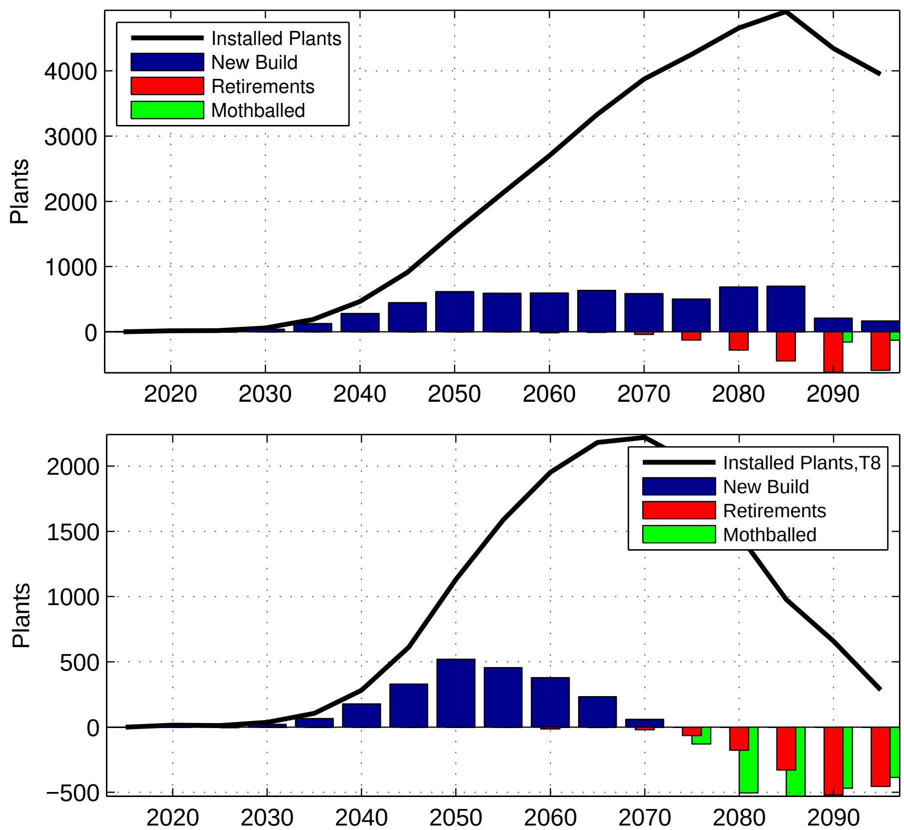

Figure S22: Deployment of coal CCS. Top assumes BECCS is not available (base case scenario). Bottom assumes BECCS is available.

H Additional results: effects of policies

The main text includes results and discussion of the effects of R&D, subsidies and carbon prices on CCS abatement and costs. We include several supplemental analyses here. In Fig. S23 we show the effects of carbon prices and R&D on cumulative abatement. In this case all parameters vary across their full ranges. A linear function us fitted to the data for carbon prices.

In Fig. S24 we fix the model parameters at their base values; the variation in each panel is limited to that within the policy shown. The one additional sources of variation is that feasibility of each technology is allowed to vary in each instance; thus their are two clusters of y-axis values. The top row of panels shows the effect of carbon prices, the middle row shows the effect of R&D, and the bottom row shows the effect of subsidies. The left column of panels shows the effect on cumulative abatement and the right column of panels shows the effect on abatement costs. Fig. S25 presents a similar analysis to Fig. S24, but it allows other parameters to vary across their full range. In Fig. S26 policies vary simultaneously, rather than one at a time as in Fig. S24 and Fig. S25. As in the previous 2 figures, all parameters vary. Linear functions are fitted to the data for carbon prices and subsidies.

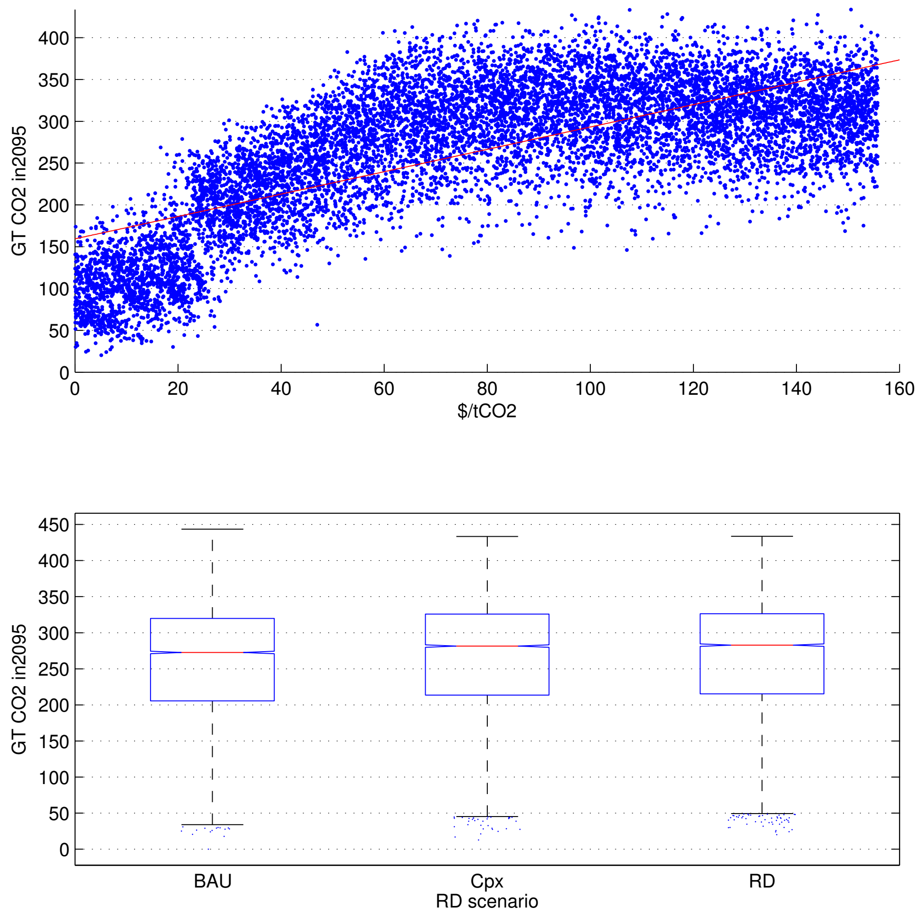

Figure S23: Effects of policy instruments on CO_2 avoided. Top: carbon price in 2040 and bottom: R&D scenario.

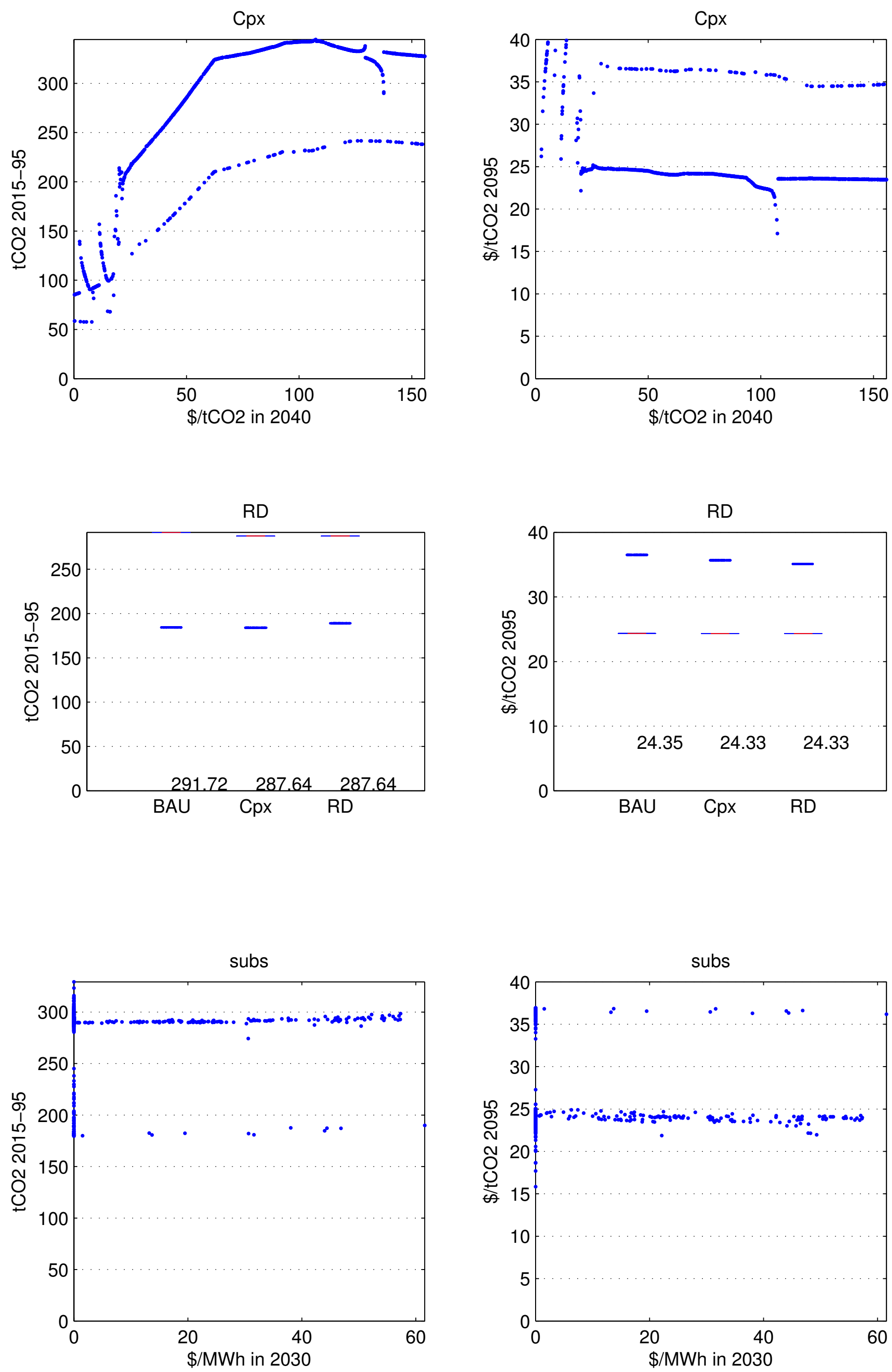

Figure S24: Effects of carbon prices (top), R&D (middle), and subsidies (bottom) on cumulative abatement (left) and abatement costs in 2050 (right) with other parameters fixed at base values.

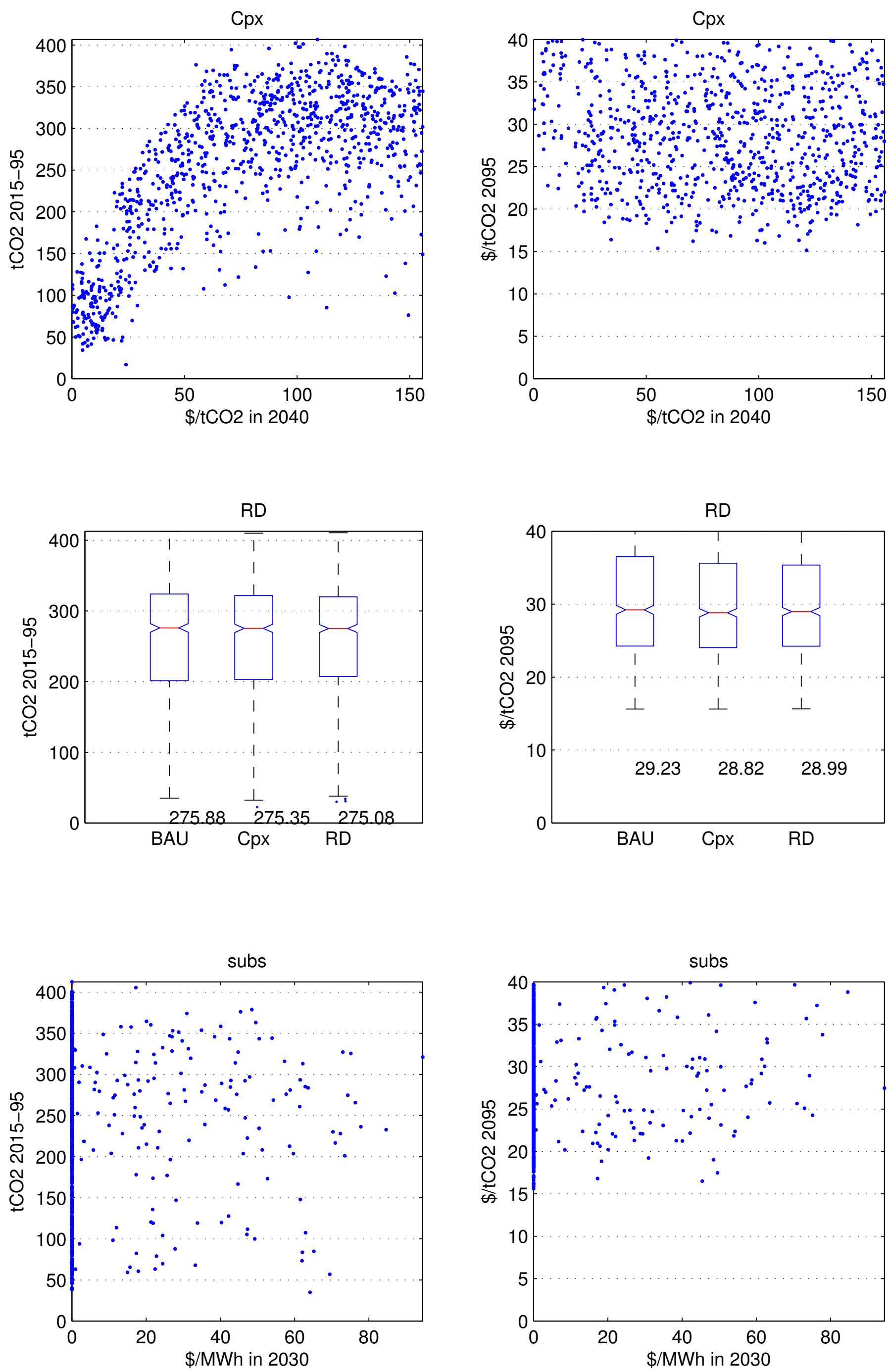

Figure S25: Effects of carbon prices (top), R&D (middle), and subsidies (bottom) on cumulative abatement (left) and abatement costs in 2050 (right) with other parameters varying.

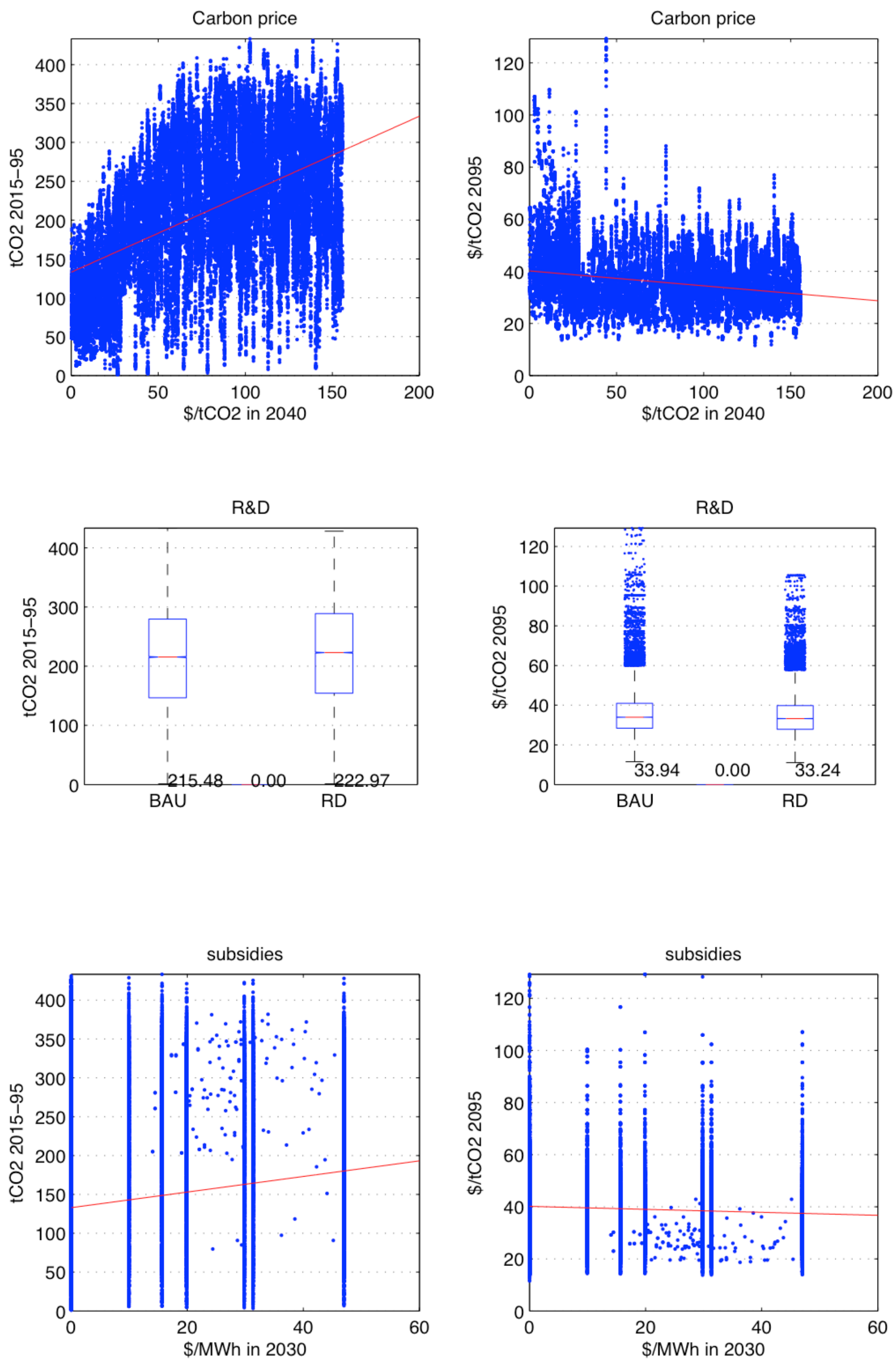

Figure S26: Effects of 2040 carbon prices (top), R&D (middle), and 2030 subsidies (bottom) on cumulative abatement (left) and abatement costs in 2050 (right) with other parameters varying.

Table S4: Optimal policy combinations under varying decision rules.

Rule:	Value	R&D scen.	Initial subsidy ($/MWh)	Subsidy decline rate	Subsidy floor ($/MWh)	Subsidy begin year
Abatement (Gt CO2) 2025–95						
Maximax	433	low	20	0.05	20	2075
Max(median)	270	high	40	0.05	10	2050
Maximin	72	high	60	0.15	30	2075
max(p≥ 300)	0.39	low	20	0.15	30	2050
Abatement cost ($/tCO2) in 2050						
Minimin	14	high	20	0.05	10	2050
Min(median)	35	high	20	0.15	30	2050
Minimax	92	high	20	0.05	10	2025
max(p≤ 30)	0.30	high	20	0.15	10	2075

I Policy combinations under decision rules

As an exploration of the results, we search across combinations of policy design components that best satisfy several possible social goals. For each policy combination, we run 1000 iterations of the assumptions shown in Fig. S13. We consider both abatement and abatement cost. For abatement our four objectives are to maximize: 1) abatement, 2) median abatement over 1000 iterations, 3) the minimum level of abatement over 1000 iterations, and 4) the probability of achieving a policy target of 300 GT. The objectives for abatement costs are similar but involve minimizing costs and the policy target is $30/t$CO_2$.

Table S4 summarizes the results and the ESM provides graphical depictions. Under most decision rules, the high R&D scenario is preferable, although two exceptions exist. The exceptions are paired with late period subsidies, suggesting that these cases may involve some very high economies of scale that may be preferable to more steady growth. Some subsidies are always preferable to none; but only low or moderate levels are needed. The subsidy floor is either at the low or middle of the range. As discussed above, mid to late-century subsidies are preferable. The one exception is in trying to avoid the worst abatement cost outcomes (minimax), in which case early subsidies are needed. This result is similar to that of Nemet and Baker (2009) on solar power, which concluded subsidies are most effective as an insurance policy against the worst outcomes.

J Timing and levels of subsidies

As discussed in the main text, we find that subsidies have only small effects on abatement and abatement costs. Here, we add some additional perspectives on the effects of subsidies. Subsidies are calculated based on 4 parameters: the year at which they begin, an initial value at the year at which they begin ($0–30/MWh), the rate at which the subsidy declines (1–30%), and a lower limit below which the subsidy no longer applies ($20–50/MWh). First, fixing the parameters shown in Fig. S13 at their base values we vary the 4 parameters affecting subsidy levels (Fig. S27). Second, Fig. S28 shows similar results but allowing the parameters in Fig. S13 to vary. Using the regression lines shown In Fig. S13 one can see that abatement is: increasing in the start year; insensitive to the start level; increasing in the decline rate; and decreasing in the floor level.

One result that is perhaps counter-intuitive is that some subsidies appear to *reduce* long-term demand for CCS electricity and abatement. This has to do with the timing of subsidies and the benefits from concentrating CCS plant construction in a short period rather than spreading this out over decades. The following figures attempt to show why this is the case. We set up 3 subsidy regimes to demonstrate the effects of timing of subsidies. Fig. S29 shows CCS costs, technological change, deployment, and abatement with $10/MWh subsidies in place for 2025–2040. Fig. S30 shows CCS costs, technological change, deployment, and abatement with $10/MWh subsidies in place for 2045–2060. Fig. S31 shows CCS costs, technological change, deployment, and abatement with $10/MWh subsidies in place for 2065–2080. Only mid and late subsidies increase deployment and abatement. Early subsidies shift deployment earlier but have no long-term effect on abatement. This latter result is in contrast to other studies that show that early subsidies can increase long term demand and abatement by accelerating the process of technological change (Nemet and Baker, 2009; Nemet and Brandt, 2012). The reason this result does not appear in this study can be seen in the top right panels of Figures S29–31, which show the change in capital cost in each 5-year period due to economies of scale in manufacturing CCS plants. The mid and later subsidies expand scale at opportune times so that economies of scale are enhanced in some periods and the same in others. In contrast, early subsidies merely shift some production earlier so that economies of scale are enhanced in 2030 and 2035, but are reduced in 2045. Because construction of new plants is much higher in 2045 than it is in the 2030s, the overall effect is actually an adverse one. This result may be in part because we apply no penalty to CCS construction facilities incur no penalty if operating below capacity. At least for capital cost, there is a social benefit to concentrating production in short periods to maximize economies of scale. The other factors changing, energy penalty and O&M, do not show this oscillation in technological change. But since they account for a smaller part of costs, the capital cost effect dominates.

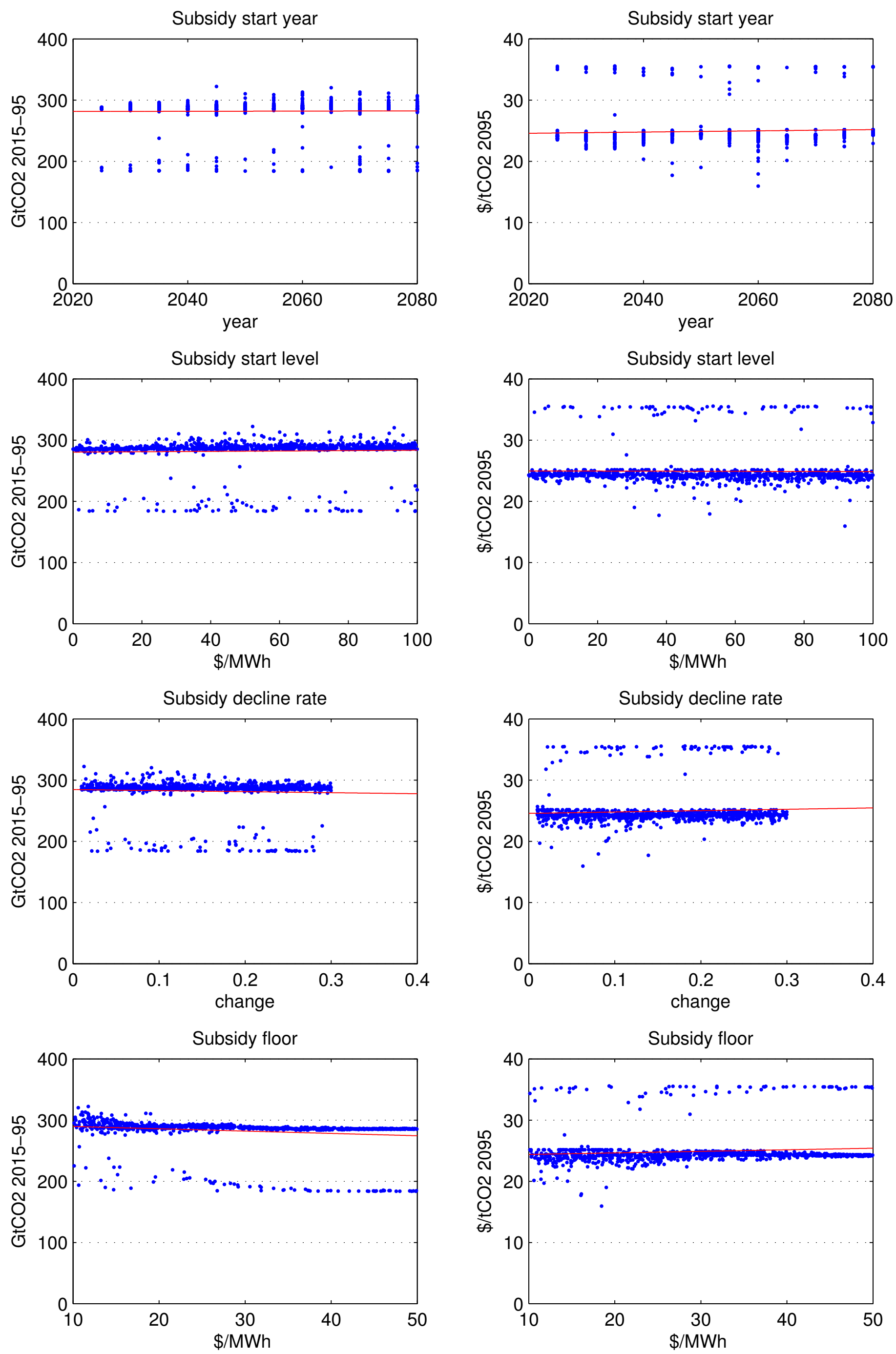

Figure S27: Effects of variation in subsidy characteristics on cumulative abatement (left) and abatement costs in 2050 (right) with other parameters fixed at base values. n=1000

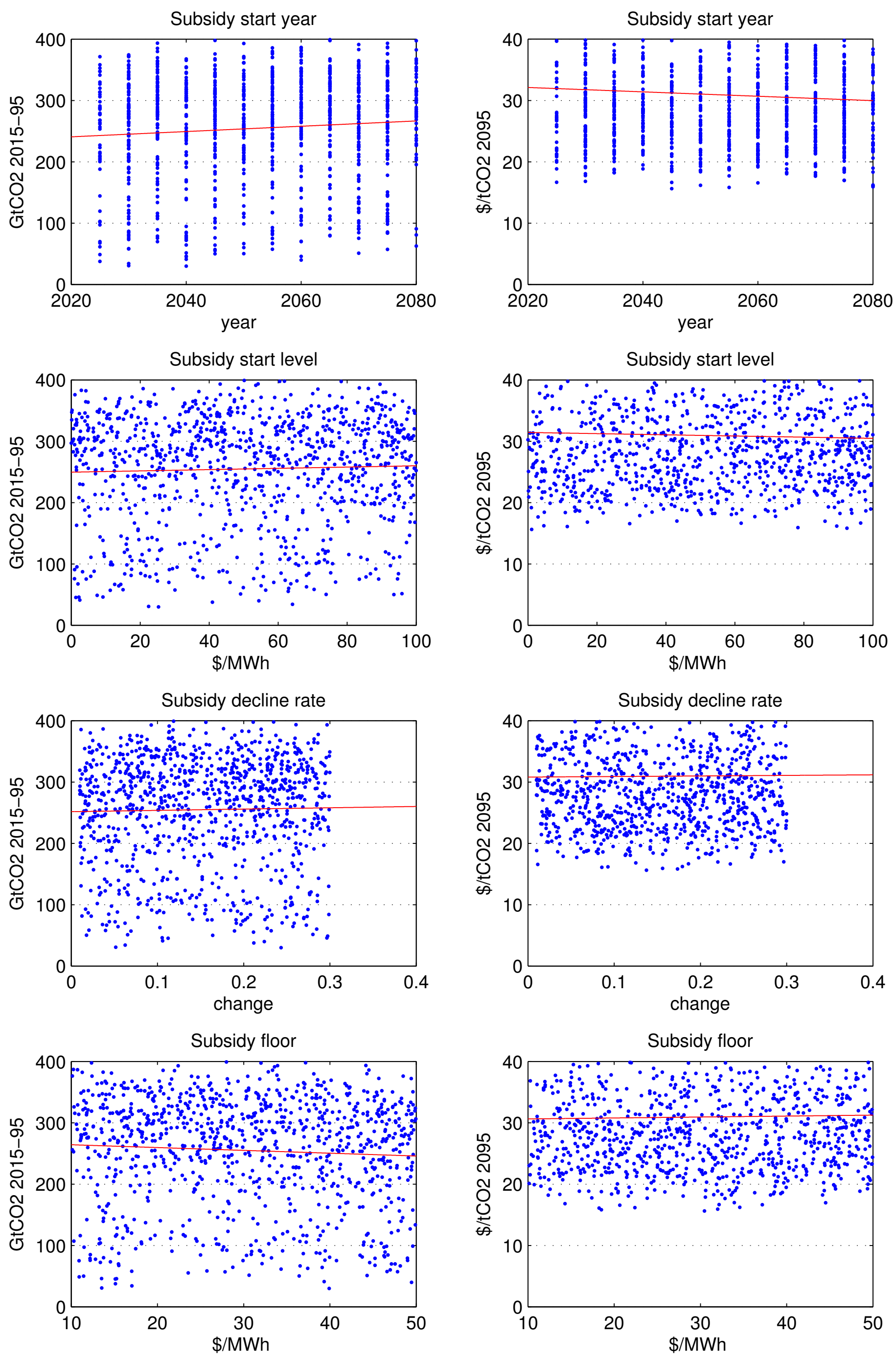

Figure S28: Effects of variation in subsidy characteristics on cumulative abatement (left) and abatement costs in 2050 (right) with other parameters varying. n=1000

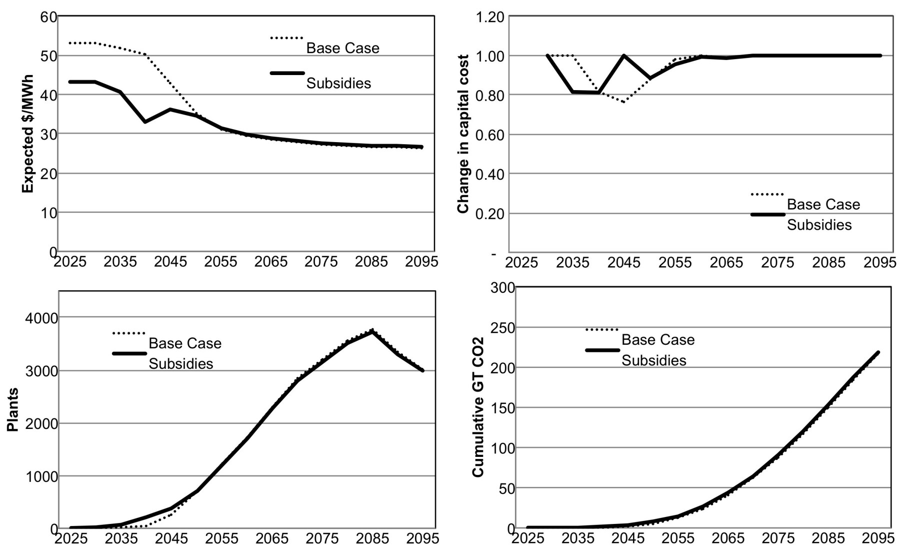

Figure S29: Early subsidies.

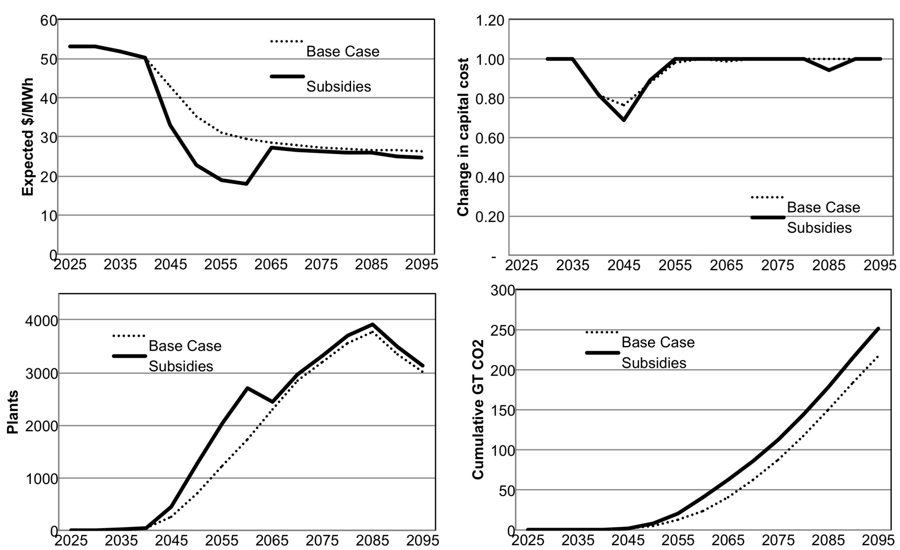

Figure S30: Mid-century subsidies.

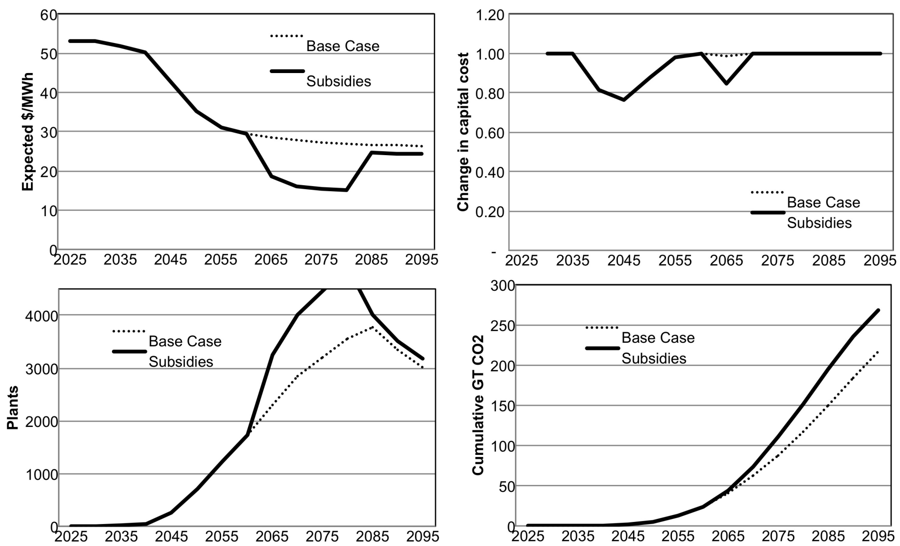

Figure S31: Late-century subsidies.

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