Supporting Information for: *Willingness to pay for a climate backstop*

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This document provides further details on the methodology and values used in this study.

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Carbon prices

Fig. S1 shows 3 pathways for carbon prices. First, we use the prices that emerge from the 'optimal' climate policy calculated by Nordhaus (2008); about \$10/tCO_2 in 2010 escalating at 2%/year. We refer to this as the 'low policy' case. Second, as our 'high policy' case, we employ the prices assumed in a recent modeling project by Johansson et al. (2009), which assumes prices starting at \$20/tCO_2 in 2010 escalating at 5%/year. Finally, as our 'mid policy' case, we use a combination of the two; \$10/tCO_2 in 2010 escalating at 5%/year. We use this 'mid policy' case as our base assumption for climate policy (Fig. S1). It is important to note that these carbon price pathways are not tied to any specific stabilization targets. For example, the low path of carbon prices is based on an optimization model (DICE-2007) that minimizes the sum of abatement costs and climate damages; it does not target a concentration level.

Deployment

We model gradual deployment of air capture over the century such that it eventually offsets a substantial portion of human emissions. Based on Pielke (2009), we assume removal of 750 gigatons of C (2.8GT of CO_2) over the course of the 21st century. A wide array of empirical case studies have found that new technologies tend to diffuse into widespread use according to a logistic function (Griliches, 1960; Mansfield, 1961; Fisher and Pry, 1971; Grubler, 1991). Adoption of technology tends to be slow early on when reliability is unproven and only early adopters risk using the new device; it accelerates as initial problems are worked out and complementary innovations enable widespread adoption; finally, diffusion slows as substitutes emerge and the market reaches saturation Rogers (1958). Based on previous work on the diffusion of innovations (Rogers, 1958; Griliches, 1960;

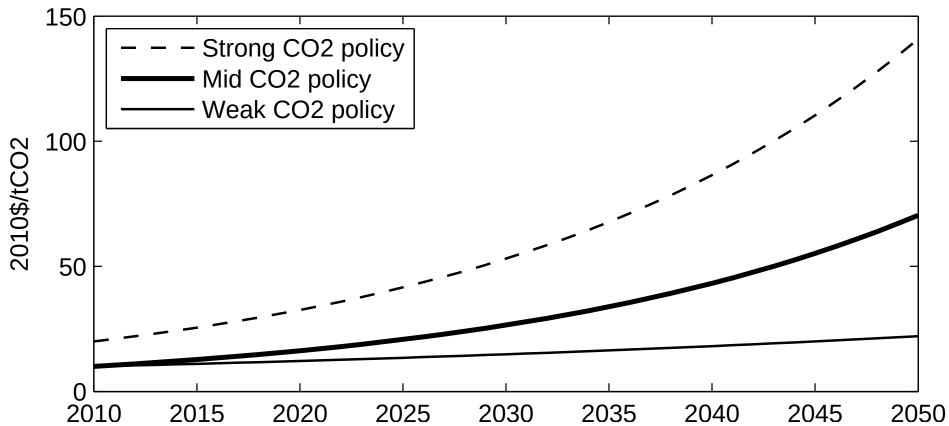

Figure S1: CO_2 prices (2010\$/tCO_2) under three assumptions about stringency of climate policy.

Mansfield, 1961; Fisher and Pry, 1971; Grubler, 1991), we apply a logistic function to model technology adoption (Fig. S2).

Research, development, and demonstration

We estimated the timing and size of a research, development and demonstration program to commercialize air capture technology. Specifying these values involves large uncertainty with only partial guidance available. Still, some analogs do exist and we make use of those to the extent they are relevant. One avenue for estimation in this area is expert elicitation, in which R&D values and outcomes are arrived at using a process that makes use of expert judgment. This method has been recommended by the National Academies (NRC, 2007) and has been successfully used for a related technology, carbon capture and sequestration (Rao et al., 2006; Baker et al., 2009; Chung et al., 2011). In the case of air capture, too few experts exist and the technology is too early stage to conduct a reliable elicitation exercise. However, the pace of interest and effort in this area is such that expertise may become sufficient to conduct such an exercise in the coming years. We thus make use of the historical analogs available in making assumptions about the timing and size of investments to fund RD&D activities.

The full RD&D program includes two components:

- *Research and Development*: The R&D program lasts for 20 years (2010–2029) with the goal to prove technical feasibility and develop

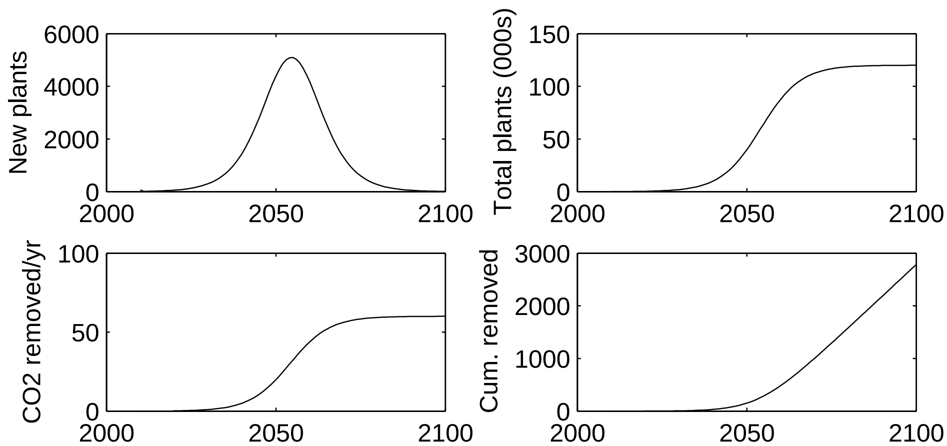

Figure S2: Deployment of air capture technology. Top: new plants installed, cumulative plants installed. Bottom: annual gigatons of CO_2 removed; cumulative gigatons of CO_2 removed.

new materials and designs that would reduce the long term costs to below the floor level described above. In the first phase (2010–2014), \$2b is invested annually to improve efficiency, and scale up the size of pilot plants. In the second phase (2015–2019) \$2b/year funds similar activities to those in phase 1 but with new focus on improving the performance of early demonstration plants, which are constructed in this period. In the third phase (2020-2029), funding is scaled down to \$1b/year as emphasis shifts to monitoring, evaluating and improving the construction and operations of full scale commercial plants that begin in 2020. The cost of the R&D program from 2010–2029 is \$30b in un-discounted 2010 dollars (present value is \$19b discounted at 7%).

The choice of a 10-year research program is based on other work looking at energy technologies in which a 10-year period is used (NRC, 2007; Nemet and Baker, 2009). The notion that R&D continues after commercialization is drawn from work on case studies of energy technologies, in which post-commercial R&D is required to address new problems that emerge at full-scale (Mitchell et al., 2011; GEA, 2011).

The levels of investment are based on historical investment levels in bringing technologies to full scale, such as fossil and nuclear (Nemet and Kammen, 2007; Gallagher et al., 2011).

The increase in funding from phase 1 to phase 2 is based on the need to increase resources as work progress toward the construction of larger and increasingly complex prototypes (GEA, 2011). The doubling in funds from phase 1 to phase 2 is taken from work on modeling R&D outcomes in CCS (Baker et al., 2009).

- *Demonstration*: Non-commercial demonstration plants are built from 2015–2019. We assume that these plants are 50% more expensive to build and operate than the first commercial plants that come on line in 2020. A wide array of empirical case studies have found that new technologies tend to diffuse into widespread use according to a logistic function (Griliches, 1960; Mansfield, 1961; Fisher and Pry, 1971; Grubler, 1991). Deployment follows this functional form because the population of early adopters, intermediate adopters, and laggards is normally distributed Rogers (1958). We use this theory of technology adoption and the resulting logistic function in Fig. S2 to estimate that 67 full scale 0.5MT/year plants will need to be built before 2020. We assume that construction of these 67 demonstration plants increases from 5 in 2015 to 32 in 2019. The cost of building these plants and operating them at full capacity until the end of 2019 is $30.6b in undiscounted 2010 dollars (present value is $18b discounted at 7%).

We also include the possibility of a limited RD&D program in which half as much is spent on R&D ($15b) and only half the demonstration plants are built ($16b). We call the full program High RD&D and the limited program Low RD&D and denote the amount of RD&D investment in net present value, R.

Effects of scale and learning by doing

We assume that capital costs for air capture plants decline with cumulative plants produced. This assumption fits with findings of learning by doing and economies of scale in production facilities (Wright, 1936; Rapping, 1965; Remer and Chai, 1990). Improvements in both O&M and energy costs accrue to learning by using (Rosenberg, 1982). As a result we assume these costs decline with the cumulative amount of CO_2 removed. The relationships between production and cost is assumed to follow a power function as in previous work on estimating the future costs of nascent energy technologies (Rubin et al., 2007; Nemet, 2009). As in previous work on the costs of

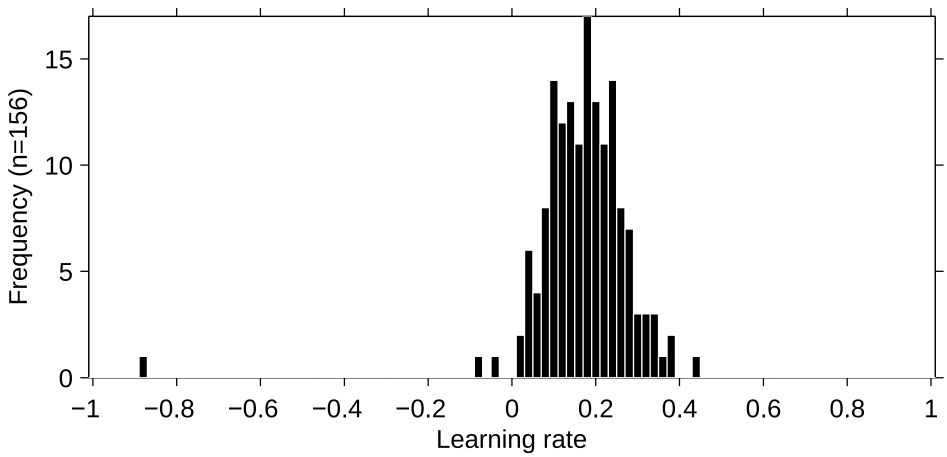

Figure S3: distribution of learning rates.

nascent technologies (Nemet, 2009), we use:

$$c_n = c_m \left(\frac{E_{n-1}}{E_m} \right)^b \tag{1}$$

where c_n is the cost at year, n and c_m is the initial cost at year m, that is where cumulative experience is E_m. We use learning rates from the previous work on carbon capture at power plants, the closest analogy for air capture (Rubin et al., 2007; van den Broek et al., 2009).

We compiled learning rates from related technologies (Fig. S3 and Table S1). Two studies estimate learning rates for an array of technologies related to CCS, such as pulverized coal plants, IGCC and pollution controls (Rubin et al., 2007; van den Broek et al., 2009). Table S1 shows these values. We calculate the median of learning rates estimated in those studies for capital and O&M and use those in our model: 0.105 for capital cost, 0.125 for O&M, which we also apply to energy use.

The value for b is related to the learning rate (L) as follows:

$$b = \frac{ln(1 - L)}{ln(2)} \tag{2}$$

producing values for b of -0.15, -0.21, and -0.21. The L values for capital cost and O&M are slightly below the mode of the distribution of historical learning rates as surveyed by Nemet (2009)(Fig. S3).

Table S1: Estimates of learning rates for technologies related to carbon capture and sequestration.

Analogous technology	Capital cost	Operations & maintenance
Flue gas desulfurization	0.110	0.220
Hydrogen steam methane reforming	0.270	0.270
Integrated coal gasification combined cycle	0.000	0.000
	0.100	0.050
	0.100	0.060
	0.110	0.220
	0.120	0.220
	0.140	0.120
Liquified natural gas	0.140	0.120
Natural gas combined cycle	0.000	0.000
	0.100	0.060
	0.100	0.060
	0.110	0.220
Oxygen production	0.100	0.050
Pulverized coal	0.000	0.000
	0.050	0.180
	0.060	0.150
	0.110	0.220
	0.120	0.220
Selective Catalytic Reduction	0.120	0.130
	0.168	0.269
Summary statistics		
mean	0.101	0.135
median	0.110	0.130
std. dev	0.060	0.092
n	21	21
max	0.270	0.270
min	0.000	0.000

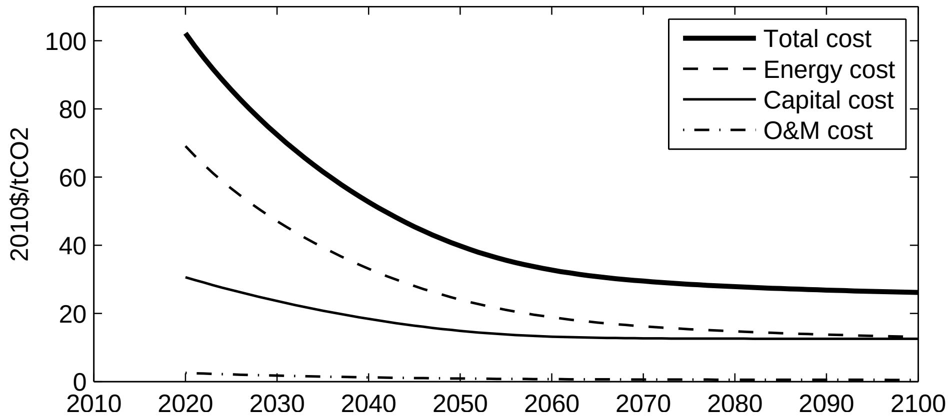

Figure S4: Components of air capture cost, under technical outcome 3 (feasible, no floor).

Air capture cost outcomes

We used a survey of existing literature on air capture costs and on leanring rates to calculate future costs of the components of air capture technology (Fig. S4). Fig. S5 shows the costs of air capture technology under 3 technical outcomes. Outcome 1 is that air capture technology is discovered to be not commercially feasible. Outcome 2 is that the technology is commercially feasible but has a lower limit on costs, below which it cannot go regardless of production-based improvements. Outcome 3 is that the technology is feasible and is not subject to the lower bound. Under our base case assumptions (outcome 2), the lower bound is reached in 2029.

Sensitivity of air capture development costs

Fig. S6 summarizes the sensitivity analysis on the costs to develop air capture. The table shows values for net present value given varying assumptions on values for input variables. The effect of CO_2 policy and discount rates are considered across changes to all other variables. Fig. S7 is similar to Table 6, but focuses on the effects of technological outcomes, rather than CO_2 policy.

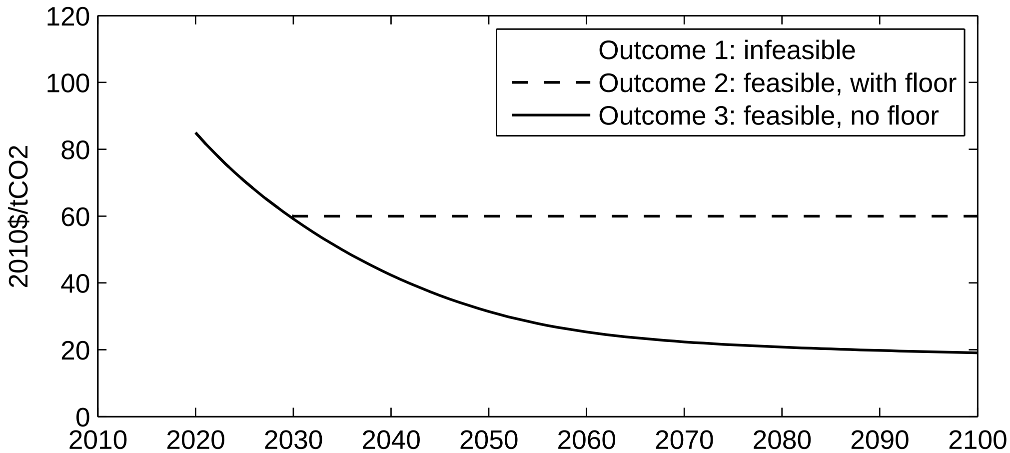

Figure S5: Costs of air capture technology under 3 technical outcomes: (1) infeasible, (2) feasible, with floor, and (3) feasible, no floor. Outcome 2 represents our base case.

Cells are net present value in $billions of sum of: Research, development, demonstration and learning investments

Variables:		**WEAK** (low CO2 prices)			**MEDIUM** (mid CO2 prices)			**STRONG** (high CO2 prices)		
1 Climate Policy:										
2 Discount rate:		2%	5%	10%	2%	5%	10%	2%	5%	10%
3 R&D outcome	Low	27	22	16	27	22	16	27	22	16
	Base	19,513	4,443	637	769	405	185	118	104	85
	High	1,954	1,129	436	394	303	191	139	124	99
4 Deployment begins	Low	19,513	4,443	637	769	405	185	118	104	85
	Base	19,513	4,443	637	769	405	185	118	104	85
	High	11,565	2,151	214	161	90	42	38	28	17
5 Floor Price ($/tCO2)	Low	2,360	1,129	421	369	283	177	114	104	85
	Base	19,513	4,443	637	769	405	185	118	104	85
	High	23,441	5,171	703	1,024	501	200	137	107	85
6 Deployment rate	Low	4,166	796	130	179	117	69	67	58	44
	Base	19,513	4,443	637	769	405	185	118	104	85
	High	34,856	9,981	1,910	3,803	1,836	674	295	234	195
7 Learning rates	Low	19,610	4,602	813	866	561	296	175	157	122
	Base	19,513	4,443	637	769	405	185	118	104	85
	High	19,501	4,424	611	757	386	158	106	85	65
8 Initial cost	Low	19,484	4,402	589	740	364	137	89	63	44
	Base	19,513	4,443	637	769	405	185	118	104	85
	High	19,957	4,841	894	1,213	800	409	394	321	218

Figure S6: Summary of sensitivity analysis for air capture model. Values are net present value of costs to develop air capture in $billions ($R + S$).

Variables:		Cells are net present value in $billions of sum of: Research, development, demonstration and learning investments								
		R&D outcome 1			**R&D outcome 2**			**R&D outcome 3**		
1 R&D outcome:		Infeasible			Feasible/$60 floor			Feasible/no floor		
2 Discount rate:		2%	5%	10%	2%	5%	10%	2%	5%	10%
3 Climate Policy	Low	27	22	16	19,513	4,443	637	1,954	1,129	436
	Base	27	22	16	769	405	185	394	303	191
	High	27	22	16	118	104	85	139	124	99
4 Deployment begins	Low	27	22	16	769	405	185	394	303	191
	Base	27	22	16	769	405	185	394	303	191
	High	22	13	6	161	90	42	155	100	47
5 Floor Price ($/tCO2)	Low	27	22	16	369	283	177	394	303	191
	Base	27	22	16	769	405	185	394	303	191
	High	27	22	16	1,024	501	200	394	303	191
6 Deployment rate	Low	27	22	16	179	117	69	179	134	84
	Base	27	22	16	769	405	185	394	303	191
	High	27	22	16	3,803	1,836	674	989	802	539
7 Learning rates	Low	27	22	16	866	561	296	832	581	310
	Base	27	22	16	769	405	185	394	303	191
	High	27	22	16	757	386	158	259	203	135
8 Initial cost	Low	27	22	16	740	364	137	180	149	108
	Base	27	22	16	769	405	185	394	303	191
	High	27	22	16	1,213	800	409	1,214	820	424

Figure S7: Summary of sensitivity analysis for air capture model. Values are net present value of costs to develop air capture in $billions ($R + S$).

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