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## The role of abatement, technology policies, and negative emission strategies in achieving climate goals<sup>\*</sup>

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#### Abstract

We model cost-minimizing portfolios of technology and emission policies for achieving year 2100 carbon dioxide (CO<sub>2</sub>) concentration targets. Technological change depends stochastically on abatement and on public funding of research and development (R&D). An analytic model shows that improving mechanisms for induced technological change has an ambiguous effect on near-term abatement and public R&D. The full numerical model shows that technology policies complement abatement while negative emission technologies can delay abatement. The type of technology targeted by public R&D depends on the level of the CO<sub>2</sub> target, and the level of public R&D funding depends on the assumed effectiveness of abatement at inducing technological change. The optimal policy portfolio almost always abates 50-100% of emissions by 2050. Announced 2°C temperature targets require greater-than-announced abatement by 2030 unless policymakers plan large-scale use of negative emission strategies or accept a substantial chance of exceeding the temperature targets.

Keywords: abatement, air capture, carbon, climate, emission, policy, portfolio, R&D, technology, uncertainty

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### 1 Introduction

The world could reach carbon dioxide (CO<sub>2</sub>) concentration targets or cumulative CO<sub>2</sub> emission targets through sustained abatement, through initial research and development (R&D) followed by greater abatement, or through use of negative emission strategies that reduce the total abatement needed. Each path requires significant and challenging long-term decarbonization, but each also implies different types of near-term policies and relies on different types of technological progress (Figure 1). The path of sustained abatement depends on early abatement to reduce the cost of later abatement. The R&D path delays abatement in the hope that an R&D program will produce new technologies that reduce the cost of future abatement. The negative emission path enables greater gross CO<sub>2</sub> emissions by using technologies that can remove previously emitted CO<sub>2</sub> from the atmosphere. The most interesting feature of negative emission strategies in our model is not that they serve as potential backstops for abatement costs but that they can separate the time of emission and the time of abatement, even potentially providing a means of decreasing atmospheric CO<sub>2</sub> concentrations.

We find that an optimal portfolio of abatement, R&D, and negative emission technologies almost invariably includes near-complete decarbonization by the middle of the 21st century, and its use of near-term abatement and public R&D funding depends on the level of the  $CO_2$  target, on the assumed feasibility of negative emission technologies, and on beliefs about the responsiveness of technological change to public R&D and to abatement. Interestingly, however, abatement decisions are not sensitive to the availability of R&D options. These optimal portfolios could serve as reference points for the global climate policy implied by international agreements and by national and subnational policies.

The next section elaborates the choice of technology and emission policies. An analytic framework then illustrates the complex dependence of optimal actions on parameters governing technological change. The full numerical model explores which policies are robust to the model's parameterization and which parameters can affect the optimal policy. We conclude with a discussion of policy implications and opportunities for further work.

## 2 Emission policies and technology policies imply different views of technological change

The multiple market failures in innovation and emission pricing mean that the welfare-maximizing climate policy almost certainly includes some combination of technology policies and emission policies [1, 2]. However, near-term climate policy can look quite different depending upon which is primary.<sup>1</sup> If emission policies are primary, then climate policy may be characterized by an economy-wide emission cap or carbon tax and a plan for how this cap or tax will change over time. Different types of emission policies provide different incentives for innovation and adoption of low-carbon technologies [4], but, in general, firms' expectations of future emission policies would determine

 $<sup>^{1}</sup>$ [3, pg. 6] well described the difference in views: "One can look at this question as whether environmental policy should come first, and be designed in a way to encourage long-run innovation, or whether technology policy needs to accompany or precede environmental policy, so as to lower the costs of implementing environmental cleanup."



Figure 1: Sample emission paths to illustrate the possible practical differences from deciding whether a policy portfolio emphasizes near-term emission abatement, near-term public R&D, or future negative emission technologies. Each path produces the same net cumulative emissions over the century and produces approximately the same  $CO_2$  concentration in the year 2100.

their budgets for low-carbon innovation. Many economic models include a version of this demandpull process of induced technological change (ITC), but there is no established way of representing it [3, 5, 6]. Governmental low-carbon technology policies may be restricted to increasing funding for basic science and reducing the perceived riskiness of new technologies (e.g., [7]).

If technology policies are primary, then climate policy may concentrate funding on an intensive search for cost-effective low-carbon technologies during a "decade of great technological experiments and failures" [8, pg. 1574]. This strategy uses technology policies to push innovation while relying on emission policies to ensure adoption of low-carbon technologies. Technology policies vary in their time horizon and in their choice of instruments. First, they can be oriented towards longterm technologies needed for anticipated deep abatement, or they can be oriented towards shorterterm technologies that reduce carbon emissions through more incremental advances. [9] concluded that increased possibility of future full abatement and increased riskiness of R&D programs often end up favoring R&D into longer-term carbon-free technologies. [10] modeled the allocation of a public R&D portfolio between efficient fossil fuel technologies, renewable energy technologies, and carbon capture and storage technologies, with the results indicating that diversification has significant value. Second, technology policies can use several instruments, including R&D subsidies, government research projects, market carve-outs, and research consortia. In the rest of this paper, we refer to R&D or technology policies generally, but we recognize that there are many nonequivalent ways of procuring R&D, innovation, and adoption and that a technology policy should itself be a portfolio of policies targeting technologies facing different types of barriers (cf. [11–14]).<sup>2</sup>

<sup>&</sup>lt;sup>2</sup>Intertwined with questions of policy design for specific classes of technologies are questions of path dependency in the larger energy system. [15] argued that climate technology policies should ensure that network effects promote

Proponents of technology policies employ several arguments against over-reliance on emission policies, all stemming from the insight that long-term climate goals require energy technology breakthroughs (e.g., [16–18]). The most developed argument against the technological effectiveness of carbon prices has two prongs: expectations of long-term carbon prices are unlikely to motivate sufficient private R&D because the government cannot credibly commit to adopting and maintaining a stringent policy into the future [19], and near-term emission prices are unlikely to be sufficiently high to motivate the needed R&D on their own [8]. Other arguments in favor of technology policies include firms' high discount rates lowering investment in long-term technologies [10], lock-in and bounded rationality limiting the space of new technologies that firms are likely to consider [20], future path dependency producing suboptimal results if policies force technologies of differing maturities to compete [8], and positive externalities emerging from the ability of technology policies to create new options for cheaper abatement [21].

Negative emission technologies could end up providing a third policy path that allows greater gross emissions to achieve the same level of net emissions. We represent large-scale negative emission technologies by air capture technologies [22].<sup>3</sup> Two leading examples are facilities that remove  $CO_2$ from the air via chemical reactions and biomass-fired electricity generators that use carbon capture and storage. The captured  $CO_2$  would be moved to geological sequestration absent another use or form of storage (e.g., [29]).<sup>4</sup> [33] used an integrated assessment model to explore the implications of air capture for climate strategy. They found that the future availability of air capture reduces near-term abatement efforts and, in the 22nd century, reduces atmospheric  $CO_2$  concentrations to pre-industrial levels faster than could have occurred via natural removal mechanisms. Our model runs include cases with and without feasible air capture in order to assess its impact on climate policy decisions, and, unlike [33], we explore how concerns about threshold effects from temporarily high  $CO_2$  levels might affect planned air capture use.

Previous analyses have explored the optimal weighting of technology policies and emission policies. In the most similar work, [34] considered six types of climate policies. They could not derive a clear welfare ranking analytically, but their numerical application to the U.S. electricity sector showed that, while an emission price is the best single policy, R&D support is an important part of the optimal portfolio. However, they explicitly focused on near-term climate policy, which does not consider the need for longer-term technological breakthroughs that motivates the above arguments for the primacy of technology policies. Our model considers longer-term emission challenges as well as the development of radical new technologies to meet these challenges.

Other models have motivated technology policies via agents with heterogeneous preferences [35], via endogenous growth models with finite patent lifetimes [36], and via intertemporal knowledge spillovers or weak patent protection [37, 38]. This literature generally finds that inability to adopt technology policies raises efficient carbon taxes to greater-than-Pigouvian levels as a means of

low-carbon technologies rather than currently entrenched technologies. [8] argued that climate technology policies should maintain a diversity of low-carbon technologies to avoid premature lock-in of a low-carbon technology that happens to have reached a more advanced level of maturity at an earlier point in time.

<sup>&</sup>lt;sup>3</sup>Other negative emission technologies proxied by air capture in this model include methods that use biological activity to sequester atmospheric  $CO_2$ , perhaps by applying biochar to soils, sending crop residues to the deep ocean, or fertilizing swathes of ocean to promote plankton blooms [23–28].

<sup>&</sup>lt;sup>4</sup>Importantly, geological sequestration of  $CO_2$  can pose its own risks, and leakage can reduce the effectiveness of air capture technologies [30–32].

compensating for the R&D shortfall. A set of studies more closely related to the current project has focused on the implications of uncertainty for portfolio selection. In one leading example, [39] found that abatement and R&D hedge against different kinds of risks produced by uncertainty about climate damages. [40] surveyed the literature on socially optimal R&D under uncertainty about damages, technology, or both. They concluded that uncertainty about damages is more important for R&D funding levels than for optimal emission levels, that it is important to model uncertainty in R&D outcomes directly rather than relying on means of distributions, and that near-term abatement and public R&D into abatement technologies are often substitutes.

Our analytic model shows how changing the effectiveness of abatement at inducing technological change can produce ambiguous effects on the level of abatement and of public R&D funding. The numerical model then extends the literature to model the simultaneous choice between emission reductions and different types of R&D policies, to consider the interaction between ITC and public R&D funding in a stochastic representation of technological change, and to include the possibility of air capture and of R&D targeted to air capture technologies.

## 3 Analytic model for jointly selecting abatement and public R&D funding

This analytic model aids intuition and shows how even a restricted version of the climate policy portfolio selection problem can depend in complex ways on estimates of ITC. [9] modeled the choice of period 1 public R&D funding when it can affect the cost of period 2 abatement, which is itself determined by the realization of a stochastic damage function, and [39] modeled the choice of abatement and R&D under anticipated learning about climate damages. We extend the R&D framework of [41] and [9] to include ITC. Abatement and public funding of R&D combine to affect the distribution of future technology outcomes. In the numerical model, these outcomes in turn affect abatement cost according to whether the new technologies are "carbon-free" technologies that help most with deep emission reductions or "emission intensity" technologies that help most at lower levels of abatement (Figure 2), but the analytic model only includes the more tractable carbon-free technological change.

We model the simultaneous first-period choice of abatement and public carbon-free R&D in the presence of ITC and of a fixed second-period greenhouse gas (GHG) concentration cap (Figure 3). GHG concentrations at the end of the second period  $(GHG_2)$  must be no greater than an exogenously specified level  $GHG^*$ . As long as the constraint  $GHG^*$  on the final GHG concentration binds and abatement costs increase in abatement, the planner selects the second-period abatement fraction  $\mu_2$  of business-as-usual second-period emissions  $e_2$  to meet the constraint  $GHG^* = (1 - \mu_2)e_2 + GHG_1$ , where  $GHG_1$  is the concentration at the end of period 1. Because  $GHG_1$  is itself the sum of the non-abated fraction  $(1 - \mu_1)$  of first-period emissions  $e_1$  and the initial concentration  $GHG_0$ , we have  $\mu_2^*(\mu_1) = (e_2 + GHG_0 + (1 - \mu_1)e_1 - GHG^*)/e_2$ .

In the first period, the planner selects abatement  $\mu_1$  and carbon-free R&D  $\bar{\alpha}_1$  to minimize current costs and discounted expected future costs. Abatement costs  $c(\mu_t, \alpha_t)$  depend on technology outcomes  $\alpha_t$ , where  $c(\mu_t, \alpha_t) = (1 - \alpha_t)c(\mu_t, 0)$  (Figure 2a).  $\bar{\alpha}_1$  is the technology target selected by public R&D funding  $g(\bar{\alpha}_1)$ . The function  $x: \{\mu, \bar{\alpha}\} \to [0, \alpha^H]$  converts abatement and the public





(a) For a given fraction  $\mu$  of emissions abated, new carbon-free technologies decrease the cost and marginal cost of abatement by a fraction  $\alpha$ , producing relatively small savings at low levels of abatement and greater savings at high levels of abatement.

(b) New emission intensity technologies reduce nonabated emissions  $(1 - \mu)$  by a fraction  $\gamma$ . They are most valuable at the lowest levels of abatement, and they can increase marginal costs at the highest levels of abatement.

Figure 2: The impact of carbon-free R&D (a) and emission intensity R&D (b), adapted from [9]. The values shown are only for illustration.



Figure 3: Influence diagram of the analytic model. Rectangles represent decisions, ovals represent stochastic nodes, and double ovals represent nodes that are deterministic functions of their input. This diagram does not show payoffs.

R&D target into a total technology target, which is bounded by no change (0) and by a maximal possible outcome ( $\alpha^H$ ). A three-point probability distribution from [9] relates actual technology outcomes to the total technology target: the total target x is achieved with probability 1 - p for exogenous p,  $\alpha^H$  is achieved with probability px, and no technological change happens with probability p(1-x). In both the analytic model and the numerical model, making the technology targets more ambitious raises the chance of achieving the greatest possible breakthrough while reducing the chance of total failure. This formulation satisfies the three recommendations of [10] for a representation of R&D: outcomes are linked stochastically to investment, it requires time to take effect, and, for properly defined funding functions, it has decreasing returns to scale in expenditures.

Substituting for  $\mu_2$  from the GHG constraint as above, the planner's objective is:

$$\min_{\mu_1,\bar{\alpha}_1} \quad c(\mu_1,0) + g(\bar{\alpha}_1) + \beta E[c(\mu_2^*(\mu_1),\alpha_2)|\mu_1,\bar{\alpha}_1] \tag{1}$$

The first-order conditions for  $\mu_1$  and  $\bar{\alpha}_1$  are:

$$\frac{\partial c(\mu_1,0)}{\partial \mu_1} = g'(\bar{\alpha}_1) \frac{\partial x(\mu_1,\bar{\alpha}_1)}{\partial \mu_1} \left[ \frac{\partial x(\mu_1,\bar{\alpha}_1)}{\partial \bar{\alpha}_1} \right]^{-1} + \beta \frac{\partial c(\mu_2^*,0)}{\partial \mu_2} \frac{e_1}{e_2} \left[ 1 - x + xp[1 - \alpha^H] \right]$$
(2)

$$g'(\bar{\alpha}_1) = \beta \frac{\partial x(\mu_1, \bar{\alpha}_1)}{\partial \bar{\alpha}_1} c(\mu_2^*, 0) [1 - p + p\alpha^H]$$

$$\tag{3}$$

where we suppress the arguments for  $\mu_2^*$  as well as for x when not in a derivative. The marginal cost of R&D funding is set equal to its discounted marginal value, determined by the reduction in abatement costs due to attaining an incrementally higher public target and to the incrementally greater chance of a maximal breakthrough. The first term on the right-hand side of equation (2) gives, analogously, the value from the R&D effect of a marginal change in abatement, and the second term gives the expected change in period 2 abatement costs due to a marginal change in period 1 abatement without accounting for effects on the R&D target.<sup>5</sup>

The first-order conditions do not lend themselves to comparative statics analysis without additional structure on the functional forms. We therefore make two simplifying assumptions. First, we assume that abatement costs and R&D costs are convex over the relevant domains, meaning that it costs more to incrementally increase abatement and technology targets when they are already at relatively high levels. Second, we assume that the marginal effects of abatement and public R&D funding on the total technology target are constant over the relevant domain (i.e.,  $\partial x/\partial \bar{\alpha}$ and  $\partial x/\partial \mu$  are constants), meaning that additional abatement and additional R&D funding each increase the total technology target by an amount that is independent of their original levels. The two assumptions together mean that the marginal cost pairs that satisfy equations (2) and (3) have slopes and curvatures as in Figure 4. Point A gives the equilibrium marginal costs, which in turn imply the optimal actions. Further, the convexity assumption allows us to interpret an increase in marginal cost as an increase in the level of the associated control variable, which means that shifts in the marginal cost equilibrium in Figure 4 have clear interpretations as shifts in the levels of the control variables.

<sup>&</sup>lt;sup>5</sup>Note that  $1 - x + xp[1 - \alpha^{H}]$  is the expected abatement cost curve as a fraction of the initial cost curve and  $1 - p + p\alpha^{H}$  is the expected technology outcome as a fraction of the total technology target.



Figure 4: An illustration of the first-order conditions in the analytic model of abatement and public carbon-free R&D funding. The x-axis is the marginal cost of period 1 abatement, and the y-axis is the marginal cost of public R&D. With the assumptions described in the text, the upward-sloping lines represent the marginal cost pairs that satisfy equation (2), and the downward-sloping lines represent the marginal cost pairs that satisfy equation (3). The dashed lines and associated equilibria B, C, D, and E show the implications of changing parameters  $(\partial x/\partial \mu, x, \alpha^H, \text{ and } p, \text{ respectively})$  that affect induced technological change and the conditional probability distribution for technological change.

Making abatement more effective at inducing technological change is a reduced-form analogue of reducing the severity of the innovation market failures that could impede the ability of a carbon price to spur low-carbon technologies. Any increase in the effectiveness of ITC must be a combination of two types of changes in the function x, but, as we will see, these component changes can have opposite effects on the decision variables. First, increasing the effectiveness of ITC may mean that an extra unit of abatement does more to increase ITC (i.e.,  $\partial x/\partial \mu$  increases). This change shifts the optimal actions to a point such as B, leading first-period abatement to increase and public R&D to decrease. Second, increasing the effectiveness of ITC may mean that every relevant level of abatement now produces more ITC. If this increase is constant (i.e., if x increases by some constant over a relevant range), public R&D increases while first-period abatement decreases. The new optimal actions are given by a point such as C. Thus, different kinds of improvement in ITC can have opposite effects. Increasing the marginal impact of abatement on the technology target causes substitution from public R&D to abatement, but increasing the level of the technology target for given levels of abatement and public R&D reduces the expected cost of later abatement, which leads to a reduction in early abatement and a partially offsetting increase in public R&D. How an increase in ITC affects abatement and public R&D depends on whether the change in ITC primarily affects the marginal contribution of abatement or primarily affects the level of technology implied by both abatement and public R&D funding.

We next consider the effects of changing the conditional distributions for technology outcomes. Increasing the maximal technology outcome  $\alpha^H$  increases public R&D (point D) because the expected outcome improves, while increasing the probability p of missing the target decreases R&D (point E) because the expected outcome worsens. Either change has an ambiguous effect on abatement. With an increase in  $\alpha^H$ , early abatement becomes more valuable as a means of obtaining R&D, but early abatement also becomes relatively more expensive because the expected cost of second-period abatement decreases. When  $\alpha^H < 1$ , increasing p reduces the expected technology outcome for a given technology target, which reduces the value of first-period abatement and R&D, but it also increases the expected second-period abatement cost curve, making first-period abatement relatively cheaper.

This analytic framing only captures the choice between abatement and a particular kind of R&D, but it already shows how optimal policies can depend in complex ways on beliefs about technological change. The numerical model produces results beyond what the analytic model can offer. It includes two kinds of R&D with ITC, and it aims to provide further intuition about how the optimal mix of climate policies may depend on beliefs about technological change and climate change.

### 4 Numerical model of policy portfolio selection

The numerical model selects the cost-minimizing level of five different climate policies in each of three periods (Figure 5). This optimal portfolio is conditional on the realizations of technology outcomes and is subject to the final  $CO_2$  concentration being no greater than an exogenous level. We solve the model using stochastic dynamic programming to obtain the optimal action in each period conditional on each possible state of the world. The periods correspond to 2010-2029, 2030-



Figure 5: Influence diagram of a non-terminal period in the numerical model. Rectangles represent decisions, ovals represent stochastic nodes, and double ovals represent nodes that are deterministic functions of their input. This diagram does not show payoffs.

2049, and 2050-2099, roughly matching the near-term, intermediate-term, and long-term periods for which  $CO_2$  emission goals are often discussed.<sup>6</sup> These large timesteps also roughly match some infrastructure lifespans, leading us to assume that abatement investment does not carry over from period to period except via its effect on technology.

The objective is to select a sequence of abatement policies  $\{\mu_t\}_{t=1}^3$ , air capture levels  $\{\kappa_t\}_{t=1}^3$ , carbon-free public R&D targets  $\{\bar{\alpha}_t\}_{t=1}^3$ , emission intensity public R&D targets  $\{\bar{\gamma}_t\}_{t=1}^3$ , and air capture public R&D targets  $\{\bar{\phi}_t\}_{t=1}^3$  so as to minimize costs while at each time period restricting the year 2100 GHG concentration  $GHG_3$  to be no greater than a predefined threshold  $GHG^*$ :

$$\min_{\{\mu,\kappa,\bar{\alpha},\bar{\gamma},\bar{\phi}\}_{t=1}^{3}} \sum_{t=1}^{3} \beta^{20(t-1)} \left[ \mu_{t} e_{t} \hat{c}(\mu_{t},\alpha_{t},\gamma_{t}) + f(\kappa_{t},\phi_{t}) + g(\frac{\bar{\alpha}_{t}}{\alpha^{H}}) + h(\frac{\bar{\gamma}_{t}}{\gamma^{H}}) + j(\bar{\phi}_{t}) \right]$$
(4)

subject to 
$$GHG_3 \le GHG^*$$
 (5)

Each of the five decision variables can have one of five levels (Table 1).  $\mu_t$  gives the fraction of business-as-usual (BAU) emissions  $e_t$  that are abated, and  $\kappa_t$  gives the quantity of air capture employed in period t. The R&D targets are evenly spaced between the maximal possible outcome and no change from the initial technology.  $\hat{c}(\cdot)$  is the average cost of abatement and depends on the fraction of BAU emissions abated ( $\mu_t$ ) and on the outcomes of previous R&D into carbon-free technologies ( $\alpha_t$ ) and emission intensity technologies ( $\gamma_t$ ).  $f(\cdot)$  gives the cost of air capture and depends on the level of air capture ( $\kappa_t$ ) and on the outcome of past air capture R&D efforts ( $\phi_t$ ).  $g(\cdot), h(\cdot)$ , and  $j(\cdot)$  give the R&D funding required by the chosen public R&D targets. The discount

 $<sup>^{6}</sup>$ We experimented with a five-period model which splits the 2050-2099 range into 3 periods. Abatement paths do not generally change, but there are more opportunities for public R&D. The cost of the policy portfolio falls as the number of periods increases because there are more chances for ITC and public R&D to produce favorable technology outcomes.

Decision variable		Possible values
Abatement	$\mu_t$	$\{0, 0.25, 0.50, 0.75, 1\}$
Air capture	$\kappa_t$	$\{0, 0.10e_3, 0.25e_3, 0.5e_3, e_3\}$
Public carbon-free R&D	$\bar{lpha}_t$	$\{0, rac{lpha^H}{4}, rac{lpha^H}{2}, rac{3lpha^H}{4}, lpha^H\}$
Public emission intensity R&D Public air capture R&D	$ar{\gamma}_t \\ ar{\phi}_t$	$ \{0, \frac{\gamma^{H}}{4}, \frac{\gamma^{H}}{2}, \frac{3\gamma^{H}}{4}, \gamma^{H}\} \\ \{1, \frac{3}{4}(1-\phi^{H}) + \phi^{H}, \frac{1}{2}(1-\phi^{H}) + \phi^{H}, \frac{1}{4}(1-\phi^{H}) + \phi^{H}, \phi^{H}\} $

Table 1: Decision variables and possible values.

factor  $\beta$  converts costs from their value at the beginning of the period in which they are incurred to their value in the prior year. Because there is no fourth period, there is no point to undertaking R&D in the third period. The appendix describes the functional forms and parameterizations used in each model scenario.

The state variable  $GHG_t$  records the CO<sub>2</sub> concentration at the end of period t and has the following transition equation:<sup>7</sup>

$$GHG_t = GHG_{t-1} + af * e_t * (1 - \mu_t) - \kappa_t \tag{6}$$

A period's final CO<sub>2</sub> concentration follows deterministically from the previous period's final concentration, the current period's emissions, and the current period's air capture. af is the airborne fraction, which gives the percentage of CO<sub>2</sub> emissions that remain in the atmosphere after a short adjustment period, and it is set as af = 0.45 [43].<sup>8</sup> We ignore the much slower longer-term decay of atmospheric CO<sub>2</sub> stocks.

The state variables  $\alpha_t$ ,  $\gamma_t$ , and  $\phi_t$  record the technology outcomes that apply to period t. As in the analytic model, these outcomes depend on probability distributions derived from [9] but

<sup>&</sup>lt;sup>7</sup>Aerosols and non-CO<sub>2</sub> greenhouse gases significantly affect the climate and have their own possibilities for mitigation [42]. The combination of technology and emission policies may be most salient for CO<sub>2</sub> because it is a long-lived GHG whose effects become important due to its accumulation over time. Since we do not include a decay term in the transition equation, a constraint on year 2100 CO<sub>2</sub> concentrations is equivalent to a constraint on twenty-first century cumulative emissions.

<sup>&</sup>lt;sup>8</sup>The airborne fraction could also work against air capture's effect on concentrations, increasing the effective cost of air capture.

adapted to include the possibility of ITC:<sup>9</sup>

$$Pr[\alpha_t = \alpha_{t-1}] = p_\alpha (1 - \min[\bar{\alpha}_{t-1} + ITC_\alpha(\mu_{t-1}), \alpha^H])$$
(7)

$$Pr[\alpha_t = \min(\bar{\alpha}_{t-1} + ITC_{\alpha}(\mu_{t-1}), \alpha^H)] = 1 - p_{\alpha}$$
(8)

$$Pr[\alpha_t = \alpha^H] = p_\alpha(\min[\bar{\alpha}_{t-1} + ITC_\alpha(\mu_{t-1}), \alpha^H])$$
(9)

$$Pr[\gamma_t = \gamma_{t-1}] = p_{\gamma}(1 - \min[\bar{\gamma}_{t-1} + ITC_{\gamma}(\mu_{t-1}), \gamma^H])$$
(10)

$$Pr[\gamma_t = \min(\bar{\gamma}_{t-1} + ITC_{\gamma}(\mu_{t-1}), \gamma^H)] = 1 - p_{\gamma}$$
(11)

$$Pr[\gamma_t = \gamma^H] = p_{\gamma}(\min[\bar{\gamma}_{t-1} + ITC_{\gamma}(\mu_{t-1}), \gamma^H])$$
(12)

$$Pr[\phi_t = \phi_{t-1}] = p_{\phi}\bar{\phi}_{t-1}$$
(13)

$$Pr[\phi_t = \bar{\phi}_{t-1}] = 1 - p_\phi \tag{14}$$

$$Pr[\phi_t = \phi^H] = p_{\phi}(1 - \bar{\phi}_{t-1})$$
(15)

We form the total technology target by summing ITC and public R&D, which assumes that publiclyfunded R&D and ITC are substitutable conditional on the type of R&D. Further, because of the long timespans covered by each period, we assume that ITC depends only on contemporary abatement and not on expectations of abatement in future periods. In the base case parameterization described in the appendix, the two functions  $ITC_{\alpha}$  and  $ITC_{\gamma}$  are defined so that low levels of abatement contribute only to emission intensity R&D while high levels of abatement can also contribute to carbon-free R&D. Any R&D prior to the first period is already incorporated into  $c(\mu_t, 0, 0)$  and  $f(\kappa_t, 1)$ , so  $\alpha_1 = \gamma_1 = 0$  and  $\phi_1 = 1$ .

Framing the CO<sub>2</sub> constraint in terms of year 2100 CO<sub>2</sub> concentrations ignores concerns about the possibility of threshold effects from temporarily overshooting the targeted concentration (e.g., [44]). We represent these concerns in a set of model runs by making the CO<sub>2</sub> constraint bind each period's concentration rather than just the third period's final concentration (i.e., equation (5) becomes  $GHG_t \leq GHG^* \forall t$ ). This change would not affect model runs in which air capture is infeasible because the inability to produce net negative emissions makes the year 2100 constraint apply to each period's final concentration. However, it could affect model runs with feasible air capture if the technology is used in later periods to make up for temporary overshoots.

The goal is to find actions that are robust to beliefs about parameters and to determine which parameters are crucial for optimal plans. We model portfolio selection for each parameter scenario under each of three different  $CO_2$  constraints. The most stringent  $CO_2$  constraint of 390 parts per million (ppm) is just above the initial  $CO_2$  concentration ( $GHG_0$ ) of 385 ppm and would be exceeded in the first period. The middling constraint of 435 ppm would be exceeded in period 2, and the least stringent constraint of 550 ppm would be exceeded in period 3. In line with insights from [45] and [46], the  $CO_2$  constraint is given exogenously based on risk preferences rather than determined endogenously using some distribution on marginal damages. If prior beliefs allow climate models to be incomplete and to share biases, then the 550 ppm target implies a 90% chance of keeping temperature change below 4°C, the 435 ppm target corresponds to requiring

<sup>&</sup>lt;sup>9</sup>In the case that  $\bar{\alpha}_{t-1} + ITC_{\alpha}(\mu_{t-1}) > \alpha^{H}$ , we have  $Pr[\alpha_{t} = \alpha^{H}] = (1 - p_{\alpha}) + p_{\alpha}\alpha^{H}$ , implying that either  $\alpha_{t} = \alpha^{H}$  or  $\alpha_{t} = \alpha_{t-1}$ . An analogous caveat holds for the probability distribution for  $\gamma$ .

a 95% chance of keeping temperature change below 4°C, and the 390 ppm target corresponds to requiring a 90% chance of keeping temperature change below 2°C [47].

### 5 Results: Robust actions and critical parameters

Figure 6 shows how planned emission paths vary by  $CO_2$  constraint, by type of options available, by concerns about tipping points, and by parameter scenarios from Table 2 in the appendix. In the absence of public R&D options, abatement provides the only means of technological change, and in the absence of feasible air capture technologies, abatement provides the only means of meeting the  $CO_2$  constraint. In our discretization, the presence of public R&D options does not tend to affect planned abatement under any of the  $CO_2$  constraints.<sup>10</sup> The 390 ppm constraint does not leave room for adjusting abatement decisions, and with the other two constraints, abatement costs are sufficiently convex that the presence of R&D options does not shift more abatement to later periods. The presence of options for negative emission air capture technologies does not affect planned actions under the 550 ppm  $CO_2$  constraint. With the 435 ppm  $CO_2$  constraint, making negative emission technologies available increases near-term abatement while decreasing long-term abatement, and with the 390 ppm  $CO_2$  constraint, it decreases near-term abatement by enabling future air capture to offset increased early emissions. The presence of a strict  $CO_2$  threshold does not greatly affect emissions under the 435 ppm  $CO_2$  constraint but increases early abatement under the 390 ppm  $CO_2$  constraint. The strict  $CO_2$  threshold also shifts some air capture use into the first period with the 390 ppm  $CO_2$  constraint in order to avoid having to abate 100% of BAU emissions in the first period.

Some policy choices are not sensitive to climate targets or to parameters' values. The optimal portfolio almost always abates at least 50% of period 2 BAU emissions and at least 75% of period 3 BAU emissions (Figures 6 and 7). Public funding for R&D is rarely above half of the maximal level,<sup>11</sup> and, unless the CO<sub>2</sub> constraint is a strict threshold or there is no discounting, air capture is almost never used before period 3 or without previous air capture R&D. A robust course of action therefore plans for deep abatement from 2030-2100, includes public R&D support that is significant but not a substitute for early abatement, and uses air capture only after deep abatement and in conjunction with ongoing deep abatement.

Carbon-free public R&D and emission intensity public R&D often substitute for each other, with expectations of future abatement driving the choice between the two types of technology forcing (Figure 7). In a subtle difference from the conclusions of [36] and of the review by [40], near-term abatement and public R&D funding do not clearly substitute for each other across scenarios. Rather, their primary determinants can push them in the same direction: near-term abatement is primarily determined by whether it is needed to keep future  $CO_2$  concentrations below the constraint, and carbon-free public R&D is primarily determined by the likelihood of future deep

 $<sup>^{10}</sup>$ [48] showed that the time path of emissions probably depends on expectations of future technology availability, but they did not model mechanisms that could influence future technologies.

<sup>&</sup>lt;sup>11</sup>The two exceptions with public R&D commonly at 75% of the maximal level are period 2 carbon-free R&D in scenarios with the 435 ppm CO<sub>2</sub> constraint and infeasible air capture and period 2 air capture R&D in scenarios with the 390 ppm CO<sub>2</sub> constraint and no strict CO<sub>2</sub> threshold.



Figure 6: The planned emission paths under the three year  $2100 \text{ CO}_2$  constraints (rows) and in the presence of different types of options and  $\text{CO}_2$  thresholds (columns). Each chart shows the business-as-usual path and the base case planned path if the only available options are for abatement. The gray lines represent the planned actions in the presence of options beyond abatement, where each gray line corresponds to one scenario from Table 2 and does not include use of negative emission technologies. The gray lines are jittered so they do not overlap. A planned action is the most likely action conditional on the previous most likely actions.



(b) Feasible air capture

Figure 7: The probability of undertaking a type of action in each parameterization. For each category of action, the three columns represent the 550 ppm  $CO_2$  constraint (left), the 435 ppm  $CO_2$  constraint (middle), and the 390 ppm  $CO_2$  constraint (right). Each dot represents a parameter combination from Table 2, and dots are jittered so they do not overlap.

abatement. These two driving factors often move together, and both are affected above all by the feasibility of air capture and the stringency of the  $CO_2$  constraint.

Knowing a few specific parameters provides many of the remaining details about the optimal course of action, regardless of other parameters' values. First, as already discussed, one of the most important parameters is the presence of options to undertake air capture use and associated R&D. The non-existence of these options is equivalent to assigning them some sufficiently high cost or to judging them too risky to consider. The possibility of air capture allows the level of period 3 abatement under the two more stringent  $CO_2$  constraints to be contingent on abatement R&D outcomes and on air capture R&D outcomes. For instance, if abatement R&D is not successful while air capture R&D is successful, air capture can be scaled up and abatement can be scaled down.<sup>12</sup> Because it reduces the probability of undertaking the deepest levels of period 2 and period 3 abatement, feasible air capture can reduce the incentive to invest in carbon-free R&D and can increase the incentive to invest in emission intensity R&D (compare Figures 8a and 8b). Air capture and emission intensity R&D thus act as complements, both substituting for carbon-free R&D and for abatement.

The  $CO_2$  constraint is another important parameter. In cases without air capture, one can almost perfectly predict each period's abatement if one knows this constraint and nothing else. The possibility of air capture tends to reduce the importance of the  $CO_2$  constraint for the determination of abatement levels and abatement R&D decisions because air capture can make the more stringent constraints' abatement goals look more like those needed for less stringent constraints. In a world without air capture, beliefs about climate change and tolerance for climate change risks almost completely determine immediate abatement and R&D decisions, and in a world with air capture, these beliefs and risk tolerance determine whether air capture is a relevant technology.

Many of the outliers that remain after accounting for the possibility of air capture and the stringency of the CO<sub>2</sub> constraint are scenarios that vary the effectiveness of ITC (i.e., vary the severity of innovation market failures). Figure 8 shows the contribution of public R&D and ITC to the period 1 total technology target in each scenario without feasible air capture.<sup>13</sup> With the 550 ppm constraint, levels of period 1 abatement are too low to provide much ITC, but emission intensity R&D receives public funding because it (and not carbon-free R&D) would pay off at relatively low levels of abatement. Interestingly, the scenario with decreased control over R&D outcomes is the only 550 ppm scenario with public carbon-free R&D, because the increased chance of a maximal breakthrough makes this type of R&D sufficiently valuable. With the 435 ppm constraint, first-period abatement is still too low to provide much ITC except in scenarios that increase ITC effectiveness, but both types of technology receive public R&D funding. With the 390 ppm constraint, first-period abatement produces high levels of ITC in all scenarios that allow ITC. Carbon-free R&D usually receives enough public funding to bring the combined technology target to the maximal level, though the scenario without ITC does not fully compensate with public R&D. Emission intensity technologies do not receive public R&D funding with the 390 ppm constraint

<sup>&</sup>lt;sup>12</sup>The quantities of air capture employed are within the range of estimates of underground global  $CO_2$  storage capacity [30], and negative emission technologies need not involve underground storage. However, captured  $CO_2$  from fossil fuel plants may compete for storage capacity with captured  $CO_2$  from negative emission facilities.

<sup>&</sup>lt;sup>13</sup>One important effect of ITC is not visible in Figure 8: in many scenarios, improving the effectiveness of ITC can increase first-period abatement. Eliminating discounting can have a similar effect.

and infeasible air capture because high levels of future abatement reduce their value.

### 6 Discussion: Policy implications and opportunities for extension

The results imply that climate policy portfolios should emphasize abatement of 50-100% by 2050 with complete decarbonization in the ensuing decades. These goals are consistent with the most ambitious goals announced by major emitters. The optimal level of near-term abatement depends on risk preferences, on beliefs about temperature change, and on beliefs about air capture, but it does not depend on the availability of technology policies. In all, a near-term target of at least 25% abatement by 2030 seems warranted as a means of keeping future options open. If future risk preferences are uncertain, then less abatement could foreclose future risk preferences from being met without large-scale air capture (and, even then, tipping point concerns could still foreclose future risk preferences). Based on the Temperature-at-Risk relationships in [47], major emitters' 2°C temperature change targets require either greater-than-announced near-term abatement beyond 50% of BAU emissions or plans for prodigious air capture use later in the century.

While the availability of technology policies generally does not affect abatement paths, it can greatly reduce the cost of the optimal policy portfolio (Figure 9). Technology policies should emphasize carbon-free technologies if air capture is not thought to be viable and if preferences are for less temperature change risk, and technology policies should emphasize emission intensity technologies if air capture is expected to play a significant role in the latter half of the century. Air capture has significant value because its feasibility can bring the cost of more ambitious  $CO_2$ targets in line with the less ambitious targets, not only saving money but making ambitious climate targets more likely to be acceptable (Figure 9). Planning for future air capture supports undertaking prior air capture R&D, though experiments without air capture R&D options show that base case planned air capture use does not depend on the availability of these options.

Strategic considerations outside the scope of this model could increase the value of technology policies relative to emission policies. First, global emissions are not determined by one government but by the combined choices of many governments. All else equal, this probably favors policies that produce cheap low-carbon technologies whose diffusion can increase other nations' interest in abating (cf. [49–52]).<sup>14</sup> Second, current governments have difficulty credibly committing to future climate policies, which may be exacerbated by the optimal portfolios' tendency to rely on significant abatement and air capture in later periods. Commitment problems can occur when the optimal actions for time s depend on whether the decision-maker is at time s or at time t < s. Such differences could arise because of changing preferences, because of the design of decision-making institutions, or because of hyperbolic discounting by decision-makers (e.g., [55]). These commitment problems could favor technology policies insofar as successful R&D outcomes make it more likely that future governments would follow through on current plans for them to undertake significant abatement.

Further work could explicitly model these strategic considerations. It could also include learning

<sup>&</sup>lt;sup>14</sup>However, technology policies may not be able to form the basis of international climate agreements, with the literature generally concluding that technology agreements could increase cooperation but would probably not be environmentally sufficient (e.g., [53, 54]).



(b) Emission intensity R&D

Figure 8: The period 1 contribution of induced technological change (ITC) and public R&D funding to the total technology target in scenarios without feasible air capture. Scenario numbers refer to Table 2. Scenarios 10 through 13 vary the effectiveness of ITC.



Figure 9: The period 1 cost of the optimal policy portfolio in the base case scenarios. Costs are given as multiples of the cost in the 435 ppm scenario with abatement as the only policy option.

about the temperature change distribution, uncertainty about future risk preferences, the possibility of each type of technology actually being a portfolio unto itself, and the possibility of other technology policies besides R&D funding. In a framework with smaller timesteps, ITC could depend on expected future abatement policies. Most immediately, further work should more thoroughly explore the parameter space by combining formal sampling methods with simplified versions of the numerical model and using exploratory data analysis techniques to analyze the results (e.g., [56, 57]). Such an analysis should also consider alternate functional forms, especially for the cost of R&D, for the effect of ITC, and for the probability distribution for technology outcomes.

Any climate policy portfolio implicitly places bets on the climatic and economic systems, but some portfolios imply more specific bets than do others and impose greater costs if their bets turn out poorly. We have taken first steps towards representing the policy implications of different types of bets and towards determining which policies cohere with the broadest range of bets. We represent aggregated drivers of random technological change in a clear framework; we avoid the calculation of marginal damages by imposing an exogenous concentration constraint based on risk preferences; and we link beliefs about climatic and economic processes to portfolio outcomes in a model that allows for complex interactions between policy options. We find that deep intermediate- and longterm abatement is part of a robust plan, but near-term abatement and R&D funding decisions depend on ultimate  $CO_2$  goals, on the feasibility of air capture technologies, and on beliefs about the effectiveness of emission policies at producing different types of technological change. 2°C temperature targets call for greater-than-proposed near-term abatement unless there are plans for significant future air capture use or unless policymakers are willing to accept a substantial chance that the targets will be exceeded. Empirical research into the technological outcomes of emission policies, theoretical research into new models of technological change, and interdisciplinary research into the possible costs and feasibility of negative emission strategies could be crucial for further

Table 2: The 15 parameter scenarios explored with the numerical model. We run each scenario with each possible combination of the three  $CO_2$  constraints, air capture feasibility, and climate tipping point concerns.

	Scenario	Parameter values	Base case values
	Base case	_	_
1	Cheap abatement	$\hat{d}(\cdot)$	$\hat{c}(\cdot)$
2	Cheap R&D	$y_g = y_j = 0.25$	$y_g = y_j = 0.50$
3	Cheap emission intensity R&D	$y_{h} = 0.50$	$y_h = 1$
4	Cheap abatement, R&D, and air capture	$\hat{d}(\cdot), x = 0.75, y_q = y_j = 0.25$	$\hat{c}(\cdot), x = 1, y_q = y_j = 0.50$
5	Limited R&D scope	$\alpha^{H} = \gamma^{H} = 0.25, \phi^{H} = 0.75$	$\alpha^{H} = \gamma^{H} = 0.75, \phi^{H} = 0.25$
6	Greater R&D scope	$\alpha^H=\gamma^H=0.95, \phi^H=0.05$	$\alpha^{H} = \gamma^{H} = 0.75, \phi^{H} = 0.25$
7	Limited R&D control	$p_{\alpha} = p_{\gamma} = p_{\phi} = 0.75$	$p_{\alpha} = p_{\gamma} = p_{\phi} = 0.25$
8	High discounting	$\beta = 0.90$	eta=0.95
9	No discounting	$\beta = 1$	eta=0.95
10	Perfect ITC	$ u_{lpha} =  u_{\gamma} = 0$	$ u_{lpha} = 0.50, \nu_{\gamma} = 0.25 $
11	Better ITC for both technologies	$ u_{lpha} = 0.25,  u_{\gamma} = 0 $	$\nu_{\alpha} = 0.50, \nu_{\gamma} = 0.25$
12	Better ITC for intensity technology	$ u_{\gamma} = 0$	$ u_{\gamma} = 0.25 $
13	No ITC	$\nu_{\alpha} = \nu_{\gamma} = 100$	$\nu_{\alpha} = 0.50, \nu_{\gamma} = 0.25$
14	Cheap air capture	x = 0.75	x = 1

constraining the optimal near-term climate policy portfolio.

### Appendix: Specification of the numerical model

This appendix describes the functional forms and parameterizations used in the numerical model (Table 2).  $\hat{c}(\mu_t, \alpha_t, \gamma_t)$  is the average cost in the base case of abating fraction  $\mu_t$  of BAU emissions  $e_t$  given R&D outcomes  $\alpha_t$  and  $\gamma_t$ :

$$\hat{c}(\mu_t, \alpha_t, \gamma_t) = \min\left[\frac{z_t}{\mu_t}\hat{c}(z, 0, 0), (1 - \alpha_t)\hat{c}(\mu_t, 0, 0)\right]$$
(16)

where  $z_t \equiv \max[(\mu_t - \gamma_t)/(1 - \gamma_t), 0]$  as in [9]. We denote the average abatement cost in the low-cost parameterization as  $\hat{d}(\mu_t, \alpha_t, \gamma_t)$ . Zero abatement costs nothing  $(c(0, \alpha_t, \gamma_t) = 0)$ , and the normalization is  $\hat{c}(1, 0, 0) = 100$ . The range of  $\hat{c}(\cdot)$  is therefore [0,100]. Figure 2 shows the effect of each type of technological change on the abatement cost curve, and the lower envelope of these new cost curves gives the average cost curve in equation (16). This representation assumes that the cheapest type of technology is used at each level of abatement.

[58] report the carbon price yielding aggregate global abatement of 25% to be between  $10/tCO_2$ and  $40/tCO_2$  and the carbon price yielding aggregate global abatement of 50% to be between  $60/tCO_2$  and some level well above  $100/tCO_2$ . We develop two marginal cost representations by assuming that: these reported carbon prices represent the marginal cost of abatement; that abatement of 25% has a marginal cost of  $20/tCO_2$ ; that abatement of 50% makes marginal costs either quintuple (base case) to  $100/tCO_2$  or triple (low-cost case) to  $60/tCO_2$ ; that higher levels of abatement follow the same geometric progression; and that the marginal cost of abating a given fraction of contemporary emissions is unaffected by previous abatement. The further assumption that marginal costs increase linearly between the discretized points allows us to identify the average cost ( $1/tCO_2$ ) at each possible level of abatement:

Base case: 
$$\hat{c}(0.25, 0, 0) = 2.4$$
,  $\hat{c}(0.50, 0, 0) = 8.4$ ,  $\hat{c}(0.75, 0, 0) = 28$ ,  $\hat{c}(1, 0, 0) = 100$   
Low-cost:  $\hat{d}(0.25, 0, 0) = 2.4$ ,  $\hat{d}(0.50, 0, 0) = 6.0$ ,  $\hat{d}(0.75, 0, 0) = 12$ ,  $\hat{d}(1, 0, 0) = 27$ 

All other cost functions in this model are expressed in terms of  $\hat{c}(\cdot)$ , the average cost of abatement in the base case. For values of  $z_t$  that fall between  $\mu$ 's discretization, we define the abatement cost functions by treating average cost as piecewise linear between the discretized points.

We assume that for any given upper limits  $\alpha^H$ ,  $\gamma^H$ , and  $\phi^H$  for R&D targets and outcomes, the funding  $g(\frac{\bar{\alpha}}{\alpha^H})$ ,  $h(\frac{\bar{\gamma}}{\gamma^H})$ , and  $j(\bar{\phi})$  that it takes to aim for the chosen public target depends not on the level of the target but on the percentage of the maximum target that it represents. In future work that might extend the model through empirical calibration, R&D costs could be treated as including opportunity costs of R&D funding and the opportunity cost of ITC could be modeled explicitly [59]. In a key simplification due to the lack of previous empirical work, we treat the cost of reaching a percentage of the maximal level of R&D as being a fraction y of the base case cost for abating the same percentage of period 1 emissions:

$$g(\frac{\bar{\alpha}}{\alpha^H}) = y_g * \hat{c}(\frac{\bar{\alpha}}{\alpha^H}, 0, 0) * \frac{\bar{\alpha}}{\alpha^H} * e_1$$
(17)

$$h(\frac{\gamma}{\gamma^H}) = y_h * g(\frac{\gamma}{\gamma^H}) \tag{18}$$

$$j(\bar{\phi}) = y_j * \hat{c}(\frac{1-\bar{\phi}}{1-\phi^H}, 0, 0) * \frac{1-\bar{\phi}}{1-\phi^H} * e_1$$
(19)

We represent carbon-free R&D costs in terms of average abatement costs because these provide a natural reference point while satisfying the desired property of decreasing returns, and we define the cost of emission intensity R&D as some fraction  $y_h$  of the cost of carbon-free R&D.

The relationship between ITC and public R&D cannot be defined using empirical results [59]. We specify the ITC functions so that 0% abatement does not affect the R&D targets and so that perfect ITC means full abatement produces an R&D target equivalent to the maximal level. We further define perfect ITC as leading a percentage abatement to produce R&D targets that are the same percentage of their maximal levels (implying  $\mu = ITC_{\alpha}(\mu)/\alpha^{H} = ITC_{\gamma}(\mu)/\gamma^{H}$  under perfect ITC). We use a parameter  $\nu$  to control the effectiveness of ITC and to proxy for the severity of innovation market failures. If  $\nu = 0$ , then ITC for that technology is perfect, and if  $\nu > 0$ , then ITC for that technology is imperfect in the sense that a percentage of full abatement does not produce an equivalent percentage of the maximal R&D target:

$$ITC_{\alpha}(\mu) = \max(0, (\mu - \nu_{\alpha})\alpha^{H})$$
(20)

$$ITC_{\gamma}(\mu) = \max(0, (\mu - \nu_{\gamma})\gamma^{H})$$
(21)

This representation enables us to vary the effectiveness of ITC across scenarios and to make ITC more effective within a given scenario for emission intensity technologies than for carbon-free technologies.

We represent air capture as having constant marginal cost, which is equal to the base case average cost of an exogenous level x of period 1 abatement:

$$f(\kappa,\phi) = \kappa\phi\,\hat{c}(x,0,0) \tag{22}$$

x = 0.75 corresponds to air capture cost of \$115/tCO<sub>2</sub>, which is near the low end of recent estimates, and x = 1 corresponds to air capture cost of \$415/tCO<sub>2</sub>, which is above many recent estimates (e.g., [22, 33, 60–62]).

BAU emissions come from scenario A2r in the International Institute for Applied System Analysis (IIASA) GGI Scenario Database (see also [63]).<sup>15</sup> Summing over each period's years yields  $e_t$  in Gt CO<sub>2</sub>:

$$e_1 = 750, e_2 = 1150, e_3 = 4500$$

The BAU path produces  $CO_2$  concentrations of 428 ppm in 2030, 493 ppm in 2050, and 749 ppm in 2100.<sup>16</sup>

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<sup>&</sup>lt;sup>15</sup>Available at: http://www.iiasa.ac.at/Research/GGI/DB/

<sup>&</sup>lt;sup>16</sup>Experiments using the lower BAU emissions from scenario B2 did not produce noteworthy differences, also indicating that the results should not be sensitive to the value of the airborne fraction. The difference between assumed BAU emission paths can represent different assumptions about population growth, the distribution of worldwide economic growth, future consumption habits, and BAU low-carbon technology adoption.

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