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The optimal portfolio of emissions abatement and low-carbon R&D depends on the expected availability of negative emission technologies

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Abstract

Combining policies to remove carbon dioxide (CO_2) from the atmosphere with policies to reduce emissions can potentially decrease CO_2 concentrations to earlier levels. We model the optimal selection of a dynamic portfolio of abatement, research and development (R&D), and negative emission policies under an exogenous CO_2 constraint and with stochastic technological change. We find that near-term abatement is not sensitive to the availability of R&D policies, but the anticipated availability of negative emission strategies can reduce near-term abatement if CO_2 targets are sufficiently ambitious. Further, planning to develop and deploy negative emission technologies can shift optimal R&D funding from breakthrough carbon-free technologies into incremental lower-carbon technologies. Importantly, when the goal is to maintain the present CO_2 concentration in the year 2100, an optimized portfolio with negative emission strategies can be 80% cheaper than an optimized portfolio lacking such strategies. However, the cost is not reduced by as much if concerns about tipping points rule out using late-century negative emission strategies to temporarily overshoot the CO_2 target earlier in the century.

1 Introduction

Business-as-usual emission paths rapidly increase carbon dioxide (CO_2) concentrations from their current level of around 390 ppm, but climatic risks are increasingly seen as justifying CO_2 targets between 350 ppm and 450 ppm. While major emitters have advocated 2°C temperature targets that may require end-of-century CO_2 concentrations towards the low end of that range (Meinshausen et al., 2009), even aggressive abatement would not hold CO_2 concentrations below 400 ppm within the century. This dilemma has spurred recent interest in additional ways of managing temperature outcomes (Lenton and Vaughan, 2009; Keith, 2009; Blackstock and Long, 2010; Kintisch, 2010). First, geoengineering techniques might reduce the temperature increase resulting from a CO_2 emission path by, for instance, reflecting more incoming solar radiation back into

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space. Second, large-scale use of negative emission technologies (NETs) can remove previously emitted atmospheric CO_2 and, if combined with aggressive emission reductions, might eventually return concentrations to safer levels. Two leading examples of NETs are air capture facilities that directly remove CO_2 from ambient air via chemical reactions and biomass-fired electricity generators that use carbon capture and storage to sequester their post-combustion CO_2.[1] By offering an alternative mitigation route, possible large-scale use of these technologies introduces flexibility into the quantity of cumulative gross emissions consistent with a given CO_2 target.

We model climate policy portfolios with options to reduce emissions, to directly fund research and development (R&D) into low-carbon technologies, and to deploy NETs. The goal is to assess how the presence of different policy options might affect optimal emission paths and policy costs. Previous analyses of optimal policy portfolios have often focused on shorter-run technological change and have not included negative emission options (e.g., Fischer and Newell, 2008), and analyses that considered NETs did not embed them in a setting with R&D options. Keith et al. (2006) used an integrated assessment model to explore how possible air capture of CO_2 affects climate strategies motivated by the possibility of abrupt climate change. They found that the future availability of air capture could reduce near-term abatement efforts but increase net long-term abatement, potentially returning atmospheric CO_2 concentrations to pre-industrial levels within 200 years. Azar et al. (2006) and Azar et al. (2010) found that bioenergy with carbon capture and storage can be quite valuable in enabling more ambitious CO_2 targets (such as 350 ppm) but is less valuable if CO_2 targets are closer to 450 ppm. Our model has less technological detail but more policy options, thereby providing insight into how NETs may influence climate policy portfolios.

We explore how NETs may influence the policy portfolio that meets an exogenous CO_2 constraint at the least expected cost. The CO_2 constraint is fixed and known in a given model run, but technological change depends stochastically on previous abatement and R&D funding and policy choices can respond to observed technological change. We first describe the numerical model for optimally selecting a climate policy portfolio in each of three periods over the 21st century. We then present the results of solving it with stochastic dynamic programming for several parameterizations and constraints. The results illustrate the implications of future negative emission options for optimal near-term abatement and R&D efforts and for the cost of policy portfolios. They also demonstrate how concerns about threshold effects from temporarily high CO_2 levels might affect the value and timing of NET deployment.

2 Model of policy portfolio optimization

We model a global decision-maker planning abatement, R&D funding, and NET deployment over the 21st century. Combining several types of policy options in one model enables interactions that might not be apparent otherwise. The decision-maker minimizes the present expected cost of her planned policies under the constraint that net cumulative emissions end up below a predetermined level, and her plans are contingent on low-carbon technological outcomes drawn from probability distributions determined by R&D funding and by abatement. In reality, global climate policy

[1] The captured CO_2 would be moved to geological sequestration absent another use or form of storage (e.g., Stephens and Keith, 2008). Other negative emission strategies include methods that use biological activity to sequester atmospheric CO_2 (Read, 2009; Woodward et al., 2009), perhaps by applying biochar to soils (Lehmann, 2007), sending crop residues to the deep ocean (Strand and Benford, 2009), or fertilizing swathes of ocean to promote plankton blooms (Smetacek and Naqvi, 2008; Strong et al., 2009).

Table 1: Key to notation for decision variables and important parameters

Symbol	Units	Description
Decision variables		
μ_t	$\frac{\text{Abated emissions}}{\text{BAU emissions}}$	Abatement
κ_t	Gt CO_2	Negative emission technology (NET) deployment
$\bar{\alpha}_t$	$\frac{\text{Reduction in abatement cost}}{\text{Initial abatement cost}}$	Technology target selected by public R&D into carbon-free technologies
$\bar{\gamma}_t$	$\frac{\text{Reduction in non-abated emissions}}{\text{Initial abatement cost}}$	Technology target selected by public R&D into emission intensity technologies
$\bar{\phi}_t$	$\frac{\text{Reduction in NETs' cost}}{\text{Initial NETs' cost}}$	Technology target selected by public R&D into NETs
Parameters		
e_t	Gt CO_2	Business-as-usual (BAU) emissions
e^*	Gt CO_2	Maximum cumulative emissions
S	–	Set of periods in which the cumulative emission constraint applies
$\alpha^H, \gamma^H, \phi^H$	Fraction (as above)	Maximal possible R&D outcomes
$\alpha_t, \gamma_t, \phi_t$	Fraction (as above)	Realized R&D outcomes
$p_\alpha, p_\gamma, p_\phi$	–	Probability of missing the R&D target
ν_α, ν_γ	Fraction (as above)	Effectiveness of abatement at inducing technological change

emerges from a game played among many decision-makers with complex objectives, but the case with a single decision-maker can provide a benchmark for establishing and assessing climate policies.

The objective is to select a sequence of abatement policies $\{\mu_t\}_{t=1}^3$, NET deployment 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 NET public R&D targets $\{\bar{\phi}_t\}_{t=1}^3$ so as to minimize discounted expected costs under a constraint e^* on cumulative CO_2 emissions (see Table 1 for a key to the notation):

$$\min_{\{\mu,\kappa,\bar{\alpha},\bar{\gamma},\bar{\phi}\}_{t=1}^3} \sum_{t=1}^{3} \beta^{20(t-1)} \left[\mu_t e_t \hat{c}(\mu_t, \alpha_t, \gamma_t) + f(\kappa_t, \phi_t) + g\left(\frac{\bar{\alpha}_t}{\alpha^H}\right) + h\left(\frac{\bar{\gamma}_t}{\gamma^H}\right) + j\left(\frac{\bar{\phi}_t}{\phi^H}\right)\right] \quad (1)$$

$$\text{subject to } \sum_{t=1}^{s} (1-\mu_t)e_t - \kappa_t \le e^*, \ \forall s \in S \quad (2)$$

The periods correspond to 2010-2029, 2030-2049, and 2050-2099, which roughly match the near-term, intermediate-term, and long-term periods for which CO_2 emission goals are often discussed. Scenarios vary the planner's access to certain types of policies by varying the possible levels that each decision variable may take (Table 2). μ_t gives the fraction of business-as-usual (BAU) emissions e_t abated in period t, and κ_t gives the quantity (Gt CO_2) of NETs deployed. Carbon-free R&D can reduce the cost of abatement by a fraction α_t, which is most valuable at greater levels of abatement, and emission intensity R&D can reduce the non-abated emissions by a fraction γ_t, which is most

Table 2: Policy options available in each scenario. Also, the cumulative CO_2 constraints applied to the option scenarios. See Table 1 for a key to the notation.

	Decision variables			Parameters	
	$\{\mu\}_{t=1}^{3}$	$\{\kappa\}_{t=1}^{3}$	$\{\bar{\alpha}, \bar{\gamma}, \bar{\phi}\}_{t=1}^{3}$ [a]	S	e^* [b]
Policy environment					
Only abatement	$\left\{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\right\}$	0	0	$\{3\}$	
+R&D	$\left\{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\right\}$	0	$\left\{0, \frac{y^H}{4}, \frac{y^H}{2}, \frac{3y^H}{4}, y^H\right\}$	$\{3\}$	
+NETs [c]	$\left\{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\right\}$	$\left\{0, \frac{e_3}{10}, \frac{e_3}{4}, \frac{e_3}{2}, e_3\right\}$	$\left\{0, \frac{y^H}{4}, \frac{y^H}{2}, \frac{3y^H}{4}, y^H\right\}$	$\{3\}$	
+Strict threshold	$\left\{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\right\}$	$\left\{0, \frac{e_3}{10}, \frac{e_3}{4}, \frac{e_3}{2}, e_3\right\}$	$\left\{0, \frac{y^H}{4}, \frac{y^H}{2}, \frac{3y^H}{4}, y^H\right\}$	$\{1, 2, 3\}$	
Constraint on CO_2					
390 ppm					88
435 ppm					880
550 ppm					2900

[a] Values shown use y as a stand-in for the variable of interest. y should be replaced by α, γ, and ϕ as appropriate.
[b] Gt CO_2
[c] Negative emission technologies

valuable at lower levels of abatement (Baker and Adu-Bonnah, 2008). R&D into NETs can reduce the cost of deploying NETs by a fraction ϕ_t. The average cost of abatement ($\hat{c}(\cdot)$) depends on the fraction of BAU emissions abated (μ_t) and on the outcomes of previous R&D into carbon-free technologies (α_t) and emission intensity technologies (γ_t). The cost of NETs ($f(\cdot)$) depends on the level of deployment (κ_t) and on the outcome of past R&D efforts (ϕ_t). R&D funding ($g(\cdot)$, $h(\cdot)$, and $j(\cdot)$) is determined by the chosen public R&D targets, and the total R&D target in a period is determined by the public R&D target and by abatement policies' induced technological change (see appendix). The discount factor β converts costs from their value at the beginning of the period in which they are incurred to their value in the prior year.

All abatement, R&D, and NET deployment is motivated by the cumulative CO_2 emission constraint e^*. This constraint can be interpreted in terms of CO_2 concentrations by assuming a constant airborne fraction of 0.45, no further stock decay, and an initial concentration of 385 ppm. We model three values for e^* (Table 2): 88 Gt CO_2 (390 ppm), 880 Gt CO_2 (435 ppm), and 2900 Gt CO_2 (550 ppm). The 550 ppm constraint may imply a 90% chance of keeping temperature change below 4°C, the 435 ppm constraint may correspond to requiring a 95% chance of keeping temperature change below 4°C, and the 390 ppm constraint may correspond to requiring a 90% chance of keeping temperature change below 2°C (Lemoine, 2010). BAU emissions come from scenario A2r in the International Institute for Applied System Analysis (IIASA) GGI Scenario

Database (see also Riahi et al., 2007).[2] Summing over each period's years yields e_t in Gt CO_2:

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

The BAU path produces CO_2 concentrations of 428 ppm in 2030, 493 ppm in 2050, and 749 ppm in 2100.[3]

Recent work has argued that 21st century cumulative emissions are a primary determinant of 21st century temperature change (Allen et al., 2009; Matthews et al., 2009). We model this viewpoint with $S = \{3\}$. However, using NETs to temporarily overshoot a cumulative emission constraint may increase concerns about causing additional irreversible changes or crossing additional tipping points (O'Neill and Oppenheimer, 2004; Lenton et al., 2008). One set of model runs represents these tipping point concerns by constraining cumulative emissions at the end of each time period with $S = \{1, 2, 3\}$ (Table 2).

The appendix describes the three-point probability distributions that determine the technology outcomes (α_t, γ_t, and ϕ_t) that apply to period t. It also describes how abatement induces technological change and defines the cost functions for abatement, NET deployment, and public R&D targets. We solve the model via backward induction for 15 reasonable parameterizations (see table in appendix), each run under 9 combinations of the constraints on cumulative emissions and available policy options (Table 2). The goal is to assess the robustness of optimal portfolios and the crucial parameters for determining those portfolios. Each model run yields the optimal policy portfolio in each period conditional on previous technological outcomes and on previous abatement and NET policies. Comparing model runs reveals the importance of R&D and negative emission options, of the CO_2 constraint, and of other key parameters.

3 Results: Portfolio cost, robust actions, and critical parameters

Tighter climate constraints require more expensive policy portfolios, but the relative cost of those portfolios depends strongly on the available policy options (Figure 1). R&D options provide the greatest cost reductions for weaker CO_2 constraints while NETs provide the greatest cost reductions for stricter constraints. R&D options provide the greatest percentage cost reductions for the weaker CO_2 constraints because these constraints permit greater flexibility in the timing of abatement and so allow abatement to be adjusted to take advantage of R&D outcomes. Including options to undertake R&D reduces the expected cost of meeting the 390 ppm constraint by almost 25%, reduces the expected cost of meeting the 435 ppm constraint by 55%, and reduces the expected cost of meeting the 550 ppm constraint by around 65%. In contrast, NETs provide the greatest expected cost reductions for the strictest CO_2 constraints because requiring greater emission reductions increases both the magnitude of NET deployment and the savings from replacing abatement. Including options to deploy NETs reduces the expected cost of the 390 ppm constraint by almost a further 80%, reduces the expected cost of the 435 ppm constraint by a further 35%, and does not further reduce the expected cost of the 550 ppm constraint. With NETs, the policy portfolio for the 390 ppm constraint costs about as much as the portfolio with R&D options for the 435 ppm constraint and about double the abatement-only portfolio for the 550 ppm constraint; however,

[2] Available at: http://www.iiasa.ac.at/Research/GGI/DB/

[3] Experiments using the lower BAU emissions from scenario B2 did not produce noteworthy differences. 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.

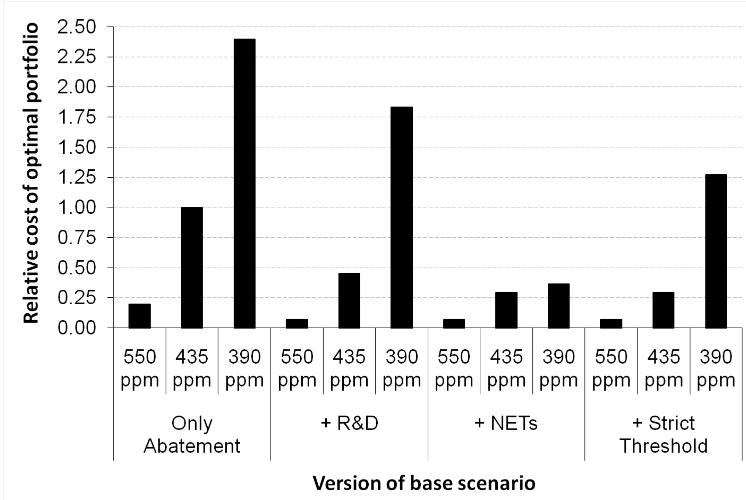


Figure 1: The present expected cost of the optimal policy portfolio in the base case scenarios. Costs are given as multiples of the cost in the 435 ppm scenario with abatement as the only policy option.

concerns about threshold effects would erode some cost savings, making the full portfolio for the 390 ppm constraint look more expensive than even the abatement-only portfolio for the 435 ppm constraint.

The presence of R&D and NET options can affect not just the cost of the policy portfolio but also the optimal emission path. The lines with circles in Figure 2 show the optimal emission path if the only policy option is to undertake abatement. The lines with the squares show the BAU emission path, which is scenario-independent. Each solid line represents the optimal gross emission path (before subtracting NETs' effects) in the modeled parameterizations, with the thickness of a line proportional to the number of represented parameterizations. Comparing the solid lines to the one with circles shows how including options changes the emission path relative to a case in which the only policy option is for abatement, comparing solid lines across columns shows the effect on optimal emissions of including additional policy options or climate threshold constraints, and comparing solid lines across rows shows the effect of the CO_2 constraint on optimal emissions.

If technology policies should be the primary component of near-term climate policy (as argued by Sandén and Azar (2005) and Montgomery and Smith (2007)), then including the option to undertake public R&D should shift abatement from earlier periods to later ones. Instead, the left column shows that this model's planned abatement paths are relatively insensitive to the availability of public R&D options (even though those options are exercised and reduce portfolio costs). In contrast, comparing the left column with the middle column shows that NET options do affect optimal emission paths: with the 435 ppm CO_2 constraint (middle row), making NETs available allows more smoothing of emissions over time by offsetting the most expensive late-century abatement, and with the 390 ppm CO_2 constraint (bottom row), NETs' availability decreases both near-term and long-term abatement by enabling future NET deployment to offset increased gross emissions.[4] Finally, comparing the right column with the middle column shows the influence of

[4]The quantities of NETs deployed are within the range of estimates of underground global CO_2 storage capacity (Benson et al., 2005), and NETs may not involve underground storage. However, captured CO_2 from fossil fuel plants may compete with captured CO_2 from negative emission facilities for end uses or storage capacity.

concerns about climate tipping points on optimal emission paths. Now the scenarios with the 390 ppm constraint (bottom row) increase both abatement and NET deployment in the first period so that CO_2 concentrations do not temporarily overshoot the target value. While NET options can reduce near-term optimal abatement, the magnitude of this effect is sensitive to concerns about crossing climate thresholds.

In a higher-level model such as the present one, the details of the control variables are less important than the big-picture story they represent. In Figure 3, we group cost-minimizing policy outcomes according to whether they produce at least 25% abatement in the first period, at least 50% abatement in the second period, 100% abatement in the third period, public funding for carbon-free R&D in any period, public funding for emission intensity R&D in any period, and deployment of NETs in any period. Interestingly, the probability of undertaking these broad categories of actions splits into probabilities near 1 and near 0. This indicates that big-picture actions are not conditional on technological outcomes, instead being driven mostly by the CO_2 constraint. The type of R&D funded depends on how much it may contribute to the broad categories of actions favored by a given combination of CO_2 constraint and available policy options: carbon-free public R&D and emission intensity public R&D often substitute for each other, with expectations of future abatement largely driving the choice between the two types of technology forcing. In a subtle difference from the conclusions of Gerlagh et al. (2009) and of the review by Baker and Shittu (2008), 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 abatement. These two driving factors often move together, and both are affected above all by the availability of NETs and the stringency of the CO_2 constraint.

Some policy choices are not sensitive to climate targets or to parameters' values. For example, the optimal portfolio almost always abates at least 50% of period 2 BAU emissions and at least 75% of period 3 BAU emissions (Figures 2 and 3). Furthermore, public funding for R&D is rarely above half of the maximal level,[5] and, unless the CO_2 constraint is a strict threshold or there is no discounting, NETs are almost never used before period 3 or without previous NET 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 deploys NETs only after deep abatement and in conjunction with ongoing deep abatement.

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 deploy NETs and undertake 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 NET use allows the precise level of period 3 abatement (as opposed to the broad categories in Figure 3) under the two more stringent CO_2 constraints to be contingent on abatement R&D outcomes and on NET R&D outcomes. For instance, if abatement R&D is not successful while NET R&D is successful, NET deployment can be scaled up and abatement can be scaled down. Because they reduce the probability of undertaking

[5]The main 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_2 constraint and unavailable NETs, period 2 emission intensity R&D in scenarios with NET options and cheap R&D or cheap abatement, and period 2 NET R&D in scenarios with the 435 or 390 ppm CO_2 constraints.

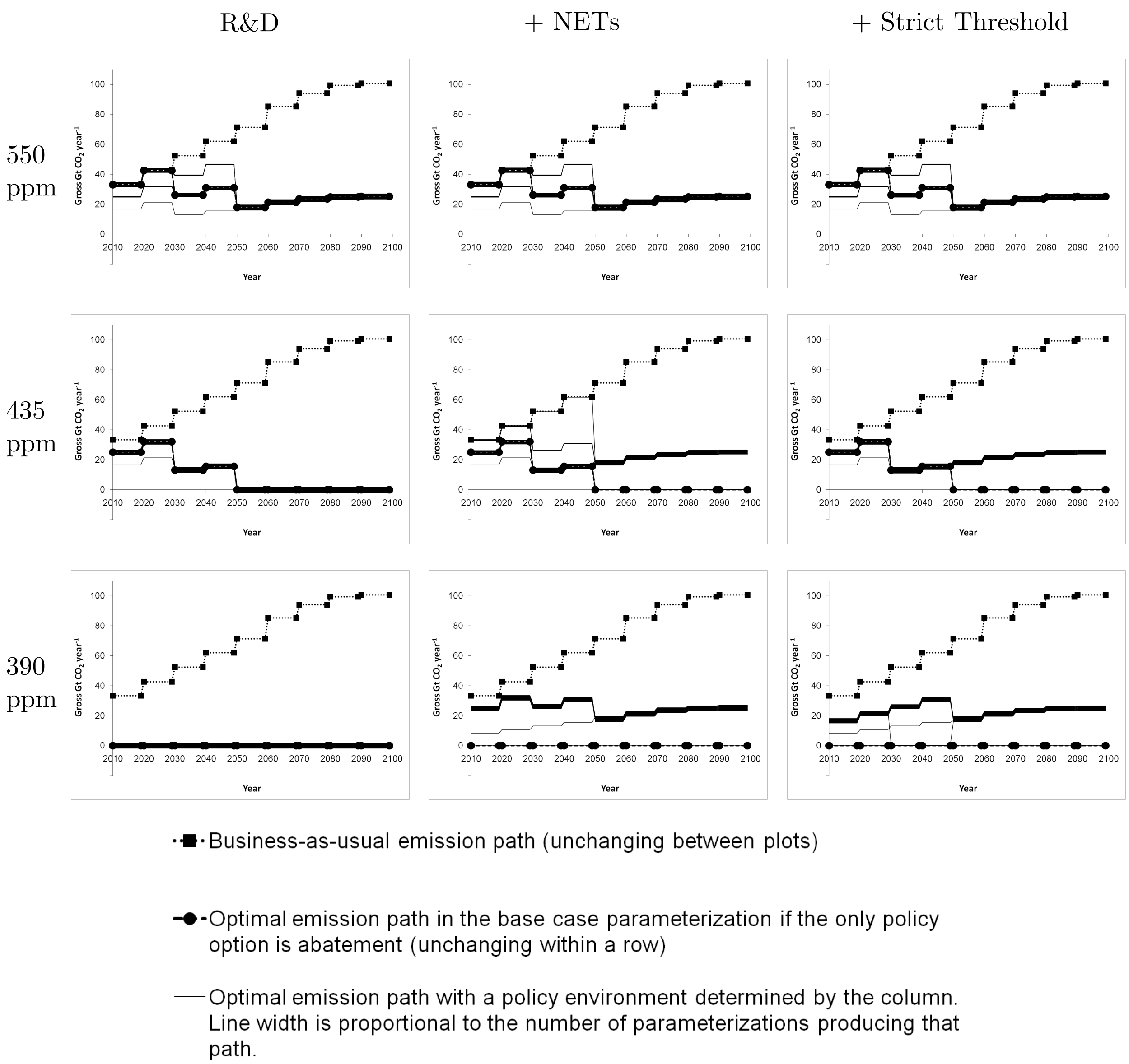
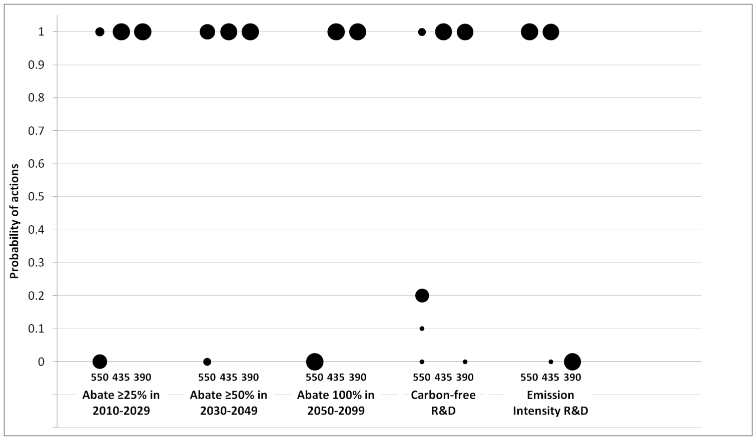
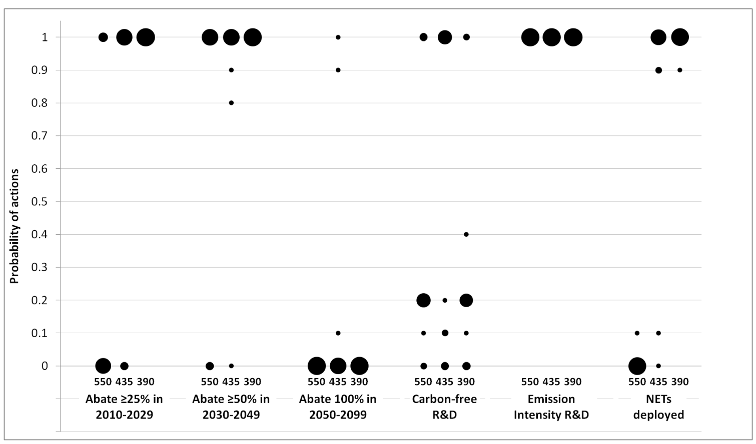


Figure 2: The planned gross emission paths (before subtracting NETs' removed CO_2) under the three year 2100 CO_2 constraints (rows) with different sets of available policy options (columns) (Table 2). Each chart shows the business-as-usual path (squares) and the base case planned path if the only available options are for abatement (circles). Each solid line represents the planned actions in the presence of options beyond abatement, where a planned action is the most likely action conditional on the previous most likely actions.



(a) NETs unavailable



(b) NETs available

Figure 3: 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 probability is rounded to the nearest multiple of 0.1, and each circle has an area proportional to the number of parameterizations producing that rounded probability.

the deepest levels of period 2 and period 3 abatement, available NETs can reduce the incentive to invest in carbon-free R&D and can increase the incentive to invest in emission intensity R&D. NETs 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.[6] In cases without available NETs, one can almost perfectly predict each period's abatement if one knows the CO_2 constraint and nothing else about the parameterization under consideration. The availability of NETs tends to reduce the importance of the CO_2 constraint for the determination of abatement levels and abatement R&D decisions because NETs can make the more stringent constraints' abatement goals look more like those needed for less stringent constraints. In a world without NETs, beliefs about climate change and tolerance for climate change risks almost completely determine immediate abatement and R&D decisions, and in a world with NETs, these beliefs and risk tolerance determine whether NETs are relevant.

4 Discussion: Policy implications

As shown by the emission paths in Figure 2 and by the probability of future deep abatement plotted in Figure 3, cost-minimizing climate policy portfolios emphasize abatement of 50-100% by 2050 in nearly all parameterizations and under almost any combination of CO_2 targets and available policy options. These levels of medium-term abatement are consistent with the most ambitious goals announced by major emitters. The optimal level of near-term abatement depends on CO_2 targets and on judgments about NETs' cost, risk, and availability, but it does not depend on the availability of policies that aim to directly spur clean energy R&D. A near-term target of at least 25% abatement by 2030 seems warranted as a means of keeping future options open, because parameterizations that produce less abatement usually use a riskier 550 ppm CO_2 constraint. If future risk preferences are uncertain, then less abatement could foreclose future risk preferences from being met without large-scale deployment of NETs (and even these would still leave vulnerability to future concerns about tipping points). Major emitters' 2°C temperature change targets may require either greater-than-announced near-term abatement beyond 50% of BAU emissions or plans for prodigious deployment of NETs later in the century.

While the availability of technology policies generally does not affect abatement paths, these policies can greatly reduce the cost of the optimal policy portfolio (Figure 1). Technology policies should emphasize carbon-free technologies if NETs are not thought to be viable and if preferences are for less temperature change risk, and technology policies should emphasize emission intensity technologies if NETs are expected to play a large role in the latter half of the century. NETs have significant value because they could bring the cost of more ambitious CO_2 targets nearer that of less ambitious targets, not only saving money but also increasing the appeal of more ambitious climate targets.

Three types of research could improve the model's applicability. First, near-term interdisciplinary research into the possible costs, scale, and land use implications of NETs could not only improve the current model but could enable future policy decisions to respond to the new information about NETs. In fact, R&D to reduce NETs' cost from the parameterized estimates almost always precedes deployment of NETs in the current model, though it does not appear to be neces-

[6]In addition, variations in the effectiveness of abatement at inducing technological change account for some variation in the level of public R&D funding.

sary for such deployment. Second, different functions for probabilistically connecting R&D support and abatement policies to technological outcomes could provide more realistic representations of technological change. However, whether or not it is empirically derived, any such function will remain subject to substantial structural uncertainty as it is applied out-of-sample to future energy R&D. This observation leads to the third important research path: the portfolio selection model might produce stronger and more detailed policy implications if, beyond its current consideration of parametric uncertainty, it also accounted for structural uncertainty about functional forms and probability distributions. This kind of sensitivity analysis may require a simpler model that runs faster, but it could provide a more complete depiction of the connection between policy outcomes and beliefs about factors governing abatement cost and technological change.

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 a step towards representing the policy implications of different types of bets and towards determining which policies cohere with the broadest range of bets. We find that deep intermediate- and long-term abatement is robust to the scenarios considered here, but near-term abatement and R&D funding decisions depend on CO_2 goals and on the anticipated availability of NETs. NETs affect optimal abatement paths if the CO_2 target is near or below present CO_2 concentrations. In that case, these options can greatly reduce the cost of the policy portfolio, and they shift some near-term funding for abatement and for radical carbon-free R&D into funding for R&D targeted towards incremental emission intensity technologies and towards reducing the cost of NETs. Future NET deployment can greatly facilitate the achievement of long-term CO_2 targets; however, planning for heavy reliance on NETs can introduce its own technological risks and may not address concerns about near-term climate thresholds and other irreversible changes.

5 Appendix: Model parameterizations

This appendix describes the parameterization of the portfolio selection model. It describes the probability distributions for technological outcomes, the functional representation of induced technological change (ITC), and the cost functions used in the objective function. First, the state variables α_t, γ_t, and ϕ_t record the technology outcomes that apply to period t (Table 1). These outcomes are each drawn from a three-point probability distribution similar to the one in Baker and Adu-Bonnah (2008). The main differences are that here the distribution is anchored by the previous period's realized outcomes and that here the targeted level of technology depends not just on the previous period's R&D funding but also on its abatement policy. Abatement can induce technological change via functions $ITC_\alpha : \mu_t \rightarrow [0, \alpha^H]$ for carbon-free R&D and $ITC_\gamma : \mu_t \rightarrow [0, \gamma^H]$ for emission intensity R&D. The technology target for a given period comes from summing the targets produced by abatement and by public R&D, provided the total target does not exceed the exogenous maximal level:[7]

$$Pr[\alpha_t = \alpha_{t-1}] = p_\alpha(1 - \min[\bar{\alpha}_{t-1} + ITC_\alpha(\mu_{t-1}), \alpha^H]) \tag{3}$$

$$Pr[\alpha_t = \min(\bar{\alpha}_{t-1} + ITC_\alpha(\mu_{t-1}), \alpha^H)] = 1 - p_\alpha \tag{4}$$

$$Pr[\alpha_t = \alpha^H] = p_\alpha(\min[\bar{\alpha}_{t-1} + ITC_\alpha(\mu_{t-1}), \alpha^H]) \tag{5}$$

$$Pr[\gamma_t = \gamma_{t-1}] = p_\gamma(1 - \min[\bar{\gamma}_{t-1} + ITC_\gamma(\mu_{t-1}), \gamma^H]) \tag{6}$$

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

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

$$Pr[\phi_t = \phi_{t-1}] = p_\phi(1 - \bar{\phi}_{t-1}) \tag{9}$$

$$Pr[\phi_t = \bar{\phi}_{t-1}] = 1 - p_\phi \tag{10}$$

$$Pr[\phi_t = \phi^H] = p_\phi \bar{\phi}_{t-1} \tag{11}$$

The ITC functions allow us to see how beliefs about the effectiveness of abatement at producing each type of technological change may affect the results. Unfortunately, the relationship between ITC and public R&D cannot be specified using empirical results (Pizer and Popp, 2008). Instead, we specify it by translating the fraction of emissions abated into the equivalent of some fraction of maximal R&D funding. First, 0% abatement does not affect the R&D targets. Second, we require perfect ITC to translate a given percentage abatement into R&D targets that are the same percentage of their maximal levels. This implies that $\mu = ITC_\alpha(\mu)/\alpha^H = ITC_\gamma(\mu)/\gamma^H$ under perfect ITC. A parameter ν controls the effectiveness of ITC and proxies 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:

$$ITC_\alpha(\mu_t) = \max(0, (\mu_t - \nu_\alpha)\alpha^H) \tag{12}$$

$$ITC_\gamma(\mu_t) = \max(0, (\mu_t - \nu_\gamma)\gamma^H) \tag{13}$$

This representation enables us to vary the effectiveness of ITC across scenarios and also to make ITC more effective within a given scenario for near-term emission intensity technologies than for longer-term carbon-free technologies. The base case parameterization assumes that ITC is stronger for near-term emission intensity technologies than for longer-term carbon-free technologies.

It remains to define cost functions for abatement, NET deployment, and public R&D targets. First, the cost of abatement depends on the level of abatement and on available technologies. $\hat{c}(\mu_t, \alpha_t, \gamma_t)$ is the average cost in the base case of abating fraction μ_t of BAU emissions e_t given R&D outcomes α_t and γ_t:

$$\hat{c}(\mu_t, \alpha_t, \gamma_t) = \min\left[\frac{z_t}{\mu_t}\hat{c}\left(z_t, 0, 0\right), (1 - \alpha_t)\hat{c}(\mu_t, 0, 0)\right] \tag{14}$$

where $z_t \equiv \max\left[(\mu_t - \gamma_t)/(1 - \gamma_t), 0\right]$ as in Baker and Adu-Bonnah (2008). In the low-cost scenario, we denote the average abatement cost by $\hat{d}(\mu_t, \alpha_t, \gamma_t)$, defined analogously to $\hat{c}(\cdot)$. 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

[7] 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 γ.

therefore [0,100]. The two terms inside the minimization operator give the effect of emission intensity technologies and carbon-free technologies, and the use of the minimization operator assumes that the cheapest type of technology is used at each level of abatement. Hoogwijk et al. (2008) reported 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 the base case and the low-cost average cost representations by assuming that marginal costs follow a geometric progression at the discretized points and increase linearly between those points.[8] This yields (\$/tCO_2):

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

When z_t falls between the above discretization for μ, we define the cost function by assuming average cost is linear between these discretized points.

A second type of cost function applies to deployment κ_t of NETs. We represent NETs as having constant marginal cost, which is determined by adjusting the base case average cost of an exogenous level x of period 1 abatement for the outcome ϕ_t of NET R&D:

$$f(\kappa_t, \phi_t) = \kappa_t(1 - \phi_t)\,\hat{c}(x, 0, 0) \tag{15}$$

$x = 0.75$ corresponds to a cost of \$115/tCO_2, which is near the low end of recent estimates, and $x = 1$ corresponds to a cost of \$415/tCO_2, which is above many recent estimates (e.g., Rhodes and Keith, 2005; Keith et al., 2006; Uddin and Barreto, 2007; Stolaroff et al., 2008; Keith, 2009; Pielke Jr., 2009).

Finally, a third type of cost function determines how much R&D funding it takes to select a technology target. We assume that the funding that it takes to aim for the chosen public target depends not on the level of the target but on the percentage of the maximal target that it represents. We treat the cost of reaching a percentage of the maximal level of R&D as being an exogenous fraction y of the base case cost for abating the same percentage of period 1 emissions:

$$g\left(\frac{\bar{\alpha}_t}{\alpha^H}\right) = y_g * \hat{c}\left(\frac{\bar{\alpha}_t}{\alpha^H}, 0, 0\right) * \frac{\bar{\alpha}_t}{\alpha^H} * e_1 \tag{16}$$
$$h\left(\frac{\bar{\gamma}_t}{\gamma^H}\right) = y_h * g\left(\frac{\bar{\gamma}_t}{\gamma^H}\right) \tag{17}$$
$$j\left(\frac{\bar{\phi}_t}{\phi^H}\right) = \frac{y_j}{y_g} * g\left(\frac{\bar{\phi}_t}{\phi^H}\right) \tag{18}$$

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 parameters in these functions and probability distributions are chosen so as to represent seemingly reasonable values, and 14 alternatives then vary one or more of these parameters to

[8] More specifically, we develop the two marginal cost representations by assuming that: the carbon prices reported in Hoogwijk et al. (2008) represent the marginal cost of abatement; abatement of 25% has a marginal cost of \$20/tCO_2; abatement of 50% makes marginal costs either quintuple (base case) to \$100/tCO_2 or triple (low-cost case) to \$60/tCO_2; higher levels of abatement follow the same geometric progression; and the marginal cost of abating a given fraction of contemporary emissions is unaffected by previous periods' abatement except through modeled technological change.

Table 3: The 15 parameter scenarios explored with the numerical model. We run each scenario with each possible combination of the three CO_2 constraints, NET availability, and climate tipping point concerns (Table 2).

Scenario	Parameter values	Base case values
Base case	–	–
Cheap abatement	$\hat{d}(\cdot)$	$\hat{c}(\cdot)$
Cheap R&D	$y_g = y_j = 0.25$	$y_g = y_j = 0.50$
Cheap emission intensity R&D	$y_h = 0.50$	$y_h = 1$
Cheap abatement, R&D, and NETs	$\hat{d}(\cdot), x = 0.75, y_g = y_j = 0.25$	$\hat{c}(\cdot), x = 1, y_g = y_j = 0.50$
Limited R&D scope	$\alpha^H = \gamma^H = \phi^H = 0.25$	$\alpha^H = \gamma^H = \phi^H = 0.75$
Greater R&D scope	$\alpha^H = \gamma^H = \phi^H = 0.95$	$\alpha^H = \gamma^H = \phi^H = 0.75$
Limited R&D control	$p_\alpha = p_\gamma = p_\phi = 0.75$	$p_\alpha = p_\gamma = p_\phi = 0.25$
High discounting	$\beta = 0.90$	$\beta = 0.95$
No discounting	$\beta = 1$	$\beta = 0.95$
Perfect ITC	$\nu_\alpha = \nu_\gamma = 0$	$\nu_\alpha = 0.50, \nu_\gamma = 0.25$
Better ITC for both technologies	$\nu_\alpha = 0.25, \nu_\gamma = 0$	$\nu_\alpha = 0.50, \nu_\gamma = 0.25$
Better ITC for intensity technology	$\nu_\gamma = 0$	$\nu_\gamma = 0.25$
No ITC	$\nu_\alpha = \nu_\gamma = 100$	$\nu_\alpha = 0.50, \nu_\gamma = 0.25$
Cheap NETs	$x = 0.75$	$x = 1$

reflect different beliefs about technological change, cost functions, or discounting (Table 3). If all parameterizations produce similar results, then we have more confidence that the results are robust to specific values. A more thorough assessment of robustness should also include structural variations in, for instance, the form of the cost functions, of the ITC functions converting abatement into R&D targets, and of the probability distribution for technological change.

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