Appendix S1. Definitions of Acronyms

$3rdG$: 3rd Generation Technologies
CCS: Carbon Capture and Storage
CDF: Cumulative Distribution Function
$ChemL$: Chemical Looping
$DICE$: Dynamic Integrated Model of Climate and the Economy
FR: Fast Burner Reactors
$GCAM$: Global Change Assessment Model
GDP: Gross Domestic Product
HTR: High Temperature Reactors
IAM: Integrated Assessment Model
$Inorg$: Inorganic Solar Cells
LWR: Light Water Reactors
MAC: Marginal Abatement Curve
Org: Organic Solar Cells
$PostC$: Post-combustion Carbon Capture
$PreC$: Pre-Combustion Carbon Capture

Appendix S2. Definitions of Variables and Parameters

Variables

$c(\mu)$: generic representation for cost of emissions abatement
$c_R(\mu)$: cost of emissions abatement in the reduced form R&D model
$D_R(\mu)$: cost of climate damages in the reduced form R&D model
$c_D(\mu_t)$: cost of emissions abatement in the DICE model
$D_D(\tau_t)$: cost of climate damages in the DICE model
e_t : total carbon emissions in period t
$\boldsymbol{G}_s(\cdot)$: representative function modeling the constraint set for stage s, $s = N, L$
$H(\tau_{t-1}, e_t)$: representative function linking greenhouse gas emissions to atmospheric temperature to the carbon cycle
$h(\boldsymbol{\alpha})$: shift effect in the marginal abatement curve due to technological success
$J^{\omega}_{\psi}(\cdot)$: representative function modeling the constraint ψ for scenario ω
k_t : capital stock in period t
l_t : investment in traditional capital in period t
o_t : consumption of goods/services in period t
u_t : social utility in period t
$U_s(\cdot)$: social utility in stage s, $s = N, L$
x_{ijk}: 1 if project j of technology i is funded at level k in the reduced form R&D model, 0 otherwise
$\boldsymbol{x}_s$: generic vector representing all decision variables other than abatement decisions in stage s, $s = N, L$
$\boldsymbol{x}$: generic vector representing all decision variables other than abatement decisions
y_t : net output of goods/services in period t
y^g_t : unadjusted output in period t
$\boldsymbol{y}_s$: vector representing net output of goods/services in stage s, $s = N, L$
α_i: pivot effect in the marginal abatement curve due to success in technology i
μ_t : level of emissions abatement in period t
$\boldsymbol{\mu}_s$: vector representing emissions abatement decisions in stage s, $s = N, L$
$\Phi\left(c\left(\mu\right), \boldsymbol{\alpha}\right)$: functional representing cost of emissions abatement after technical change
τ_t : atmospheric temperature in period t
$\boldsymbol{\tau}_s$: vector representing atmospheric temperature in stage s, $s = N, L$
Υ_i: investment in technology category i
$\boldsymbol{\Upsilon}$: vector representing investment decisions in technologies

Parameters

$\mathcal{A}_i$: stochastic entity representing the returns function for technology category i
A_t : level of total factor productivity in period t
b^{ω}_{ψ}: representative parameter modeling the right hand side of constraint ψ for scenario ω
$\boldsymbol{b}_s$: representative vector modeling the right hand sides of constraints for stage s, $s = N, L$
$\mathcal{B}$: R&D budget
B_t : maximum cost of abatement based on the cost of a backstop technology in period t
E_t : emissions from deforestation in period t
f_{ijk}: required investment for project j of technology category i at level k in the reduced form R&D model

L_t : population and labor input in period t
p^ω: probability of scenario ω
P_t : degree of policy participation in period t
R_t : utility discount factor for period t
S_t : ratio of uncontrolled emissions to output in period t
Z: stochastic parameter modeling the magnitude of climate damages in the reduced form R&D model
α_{ij}: calculated pivot effect in the marginal abatement curve due to success in project j in technology i
β : elasticity of marginal utility of consumption
γ : elasticity of output with respect to capital
θ : cost function exponent set to 2.8 in DICE
κ : opportunity cost parameter
π : stochastic parameter modeling the magnitude of climate damages
σ : rate of depreciation of capital

Appendix S3. Summary of Expert Elicitation Results

Technology	Project	NPV of Funding (000,000)	Probability of success
Carbon Capture and Storage (CCS)	*Pre-combustion Carbon Capture (Pre C)*	$39	2.7%
		$154	11.0%
		$386	22.3%
	Chemical Looping (Chem L)	$19	8.0%
		$38	29.5%
		$56	42.0%
	Post-combustion Carbon Capture (Post C)	$52	59.0%
		$224	70.0%
		$519	78.5%

Table S3.1 Summary of expert elicitation results for the CCS technology (Baker et al. 2009b).

Technology	Project	NPV of Funding (000,000)	Probability of success
Nuclear	*Light Water Reactors (LWR)*	$173	21.3%
		$260	33.8%
		$346	60.0%
	High Temperature Reactors (HTR)	$772	0.3%
			1.2%
		$1,544	17.0%
			26.2%
		$3,089	30.2%
			40.3%
	Fast Burner Reactors (FR)	$1,158	0.1%
			7.5%
		$4,633	0.5%
			32.5%
		$15,443	16.3%
			60.0%

Table S3.2 Summary of expert elicitation results for the nuclear technology (Baker et al. 2008).

Technology	Project	NPV of Funding (000,000)	Probability of success
Solar	*Organic Solar Cells (Org)*	$116	0.0%
			13.0%
		$830	3.9%
			28.7%
	Inorganic Solar Cells (Inorg)	$39	26.7%
		$77	44.3%
	3rd Generation Technologies (3rd G)	$386	2.0%

Table S3.3 Summary of expert elicitation results for the solar technology (Baker et al. 2009a).

Different research areas in each technology are listed in the ‘Project’ column in the elicitation summary tables. The investment amount for each project can be at one of multiple potential levels. These different investment levels are listed under the ‘NPV of Funding’ column in the tables, where NPV refers to the net present value calculated at an interest rate of 5%. Each project is also associated with specific endpoints or targets to be assessed, such as a given efficiency level, which define ‘success’ for that project. The specific probabilities of success for different investment levels of each project reflect an aggregation of the individual experts’ judgments, and are shown in the last column of the tables. Note that for some of the technologies, two levels of success were defined (representing lower and higher goals such as 15% versus 31% efficiency), and therefore the funding amounts have two rows associated with them.

Appendix S4. Description of Inapplicability of Other Elicitation Data

We note that while other elicitation data exists on the three technologies we consider, they are not applicable to the type of R&D portfolio analysis studied in this paper. For example, in some of the other studies the subtechnologies or projects in each technology are not differentiated at all (National Research Council 2007, Anadon et al. 2011a, Chan et al. 2011), while in one study only one project is considered (Rao et al. 2006). In a few of the elicitations, each expert evaluated the project they thought was the most promising project (Curtright et al. 2008, Anadon et al. 2011a, Chan et al. 2011, Bosetti et al. 2012). Such data would not work very well for a general R&D analysis, as it would result in an increased level of bias in the models due to not aggregating over multiple experts. In addition, except for Anadon et al. (2011a) and Chan et al. (2011), all elicitations assume a single funding level for the technologies studied, and none of them include project cost estimates as part of the elicitations. Hence, the expert elicitation data used in our analysis represents the most appropriate currently available data for energy technology R&D portfolio policy analysis.

Appendix S5. Description of Cost of Abatement in DICE

The cost of abatement in DICE is represented by $c_D(\mu_t) = P_t^{1-\theta} B_t \mu_t^{\theta}$ where θ is set to 2.8 and $P_t^{1-\theta} B_t$ is a product of two constants with B_t modeling the maximum cost of abatement based on the cost of a "backstop" technology, and P_t representing a possible increase in the costs related to the degree of participation in a given policy. Specifically, this participation factor reflects the fact that in some of the policies considered, not all regions participate in reducing emissions, leading to a higher cost of abatement. Moreover, a backstop technology in this context is defined as a technology that would serve as a perfect substitute for exhaustible resources.

Appendix S6. Representative Marginal Abatement Cost Curves

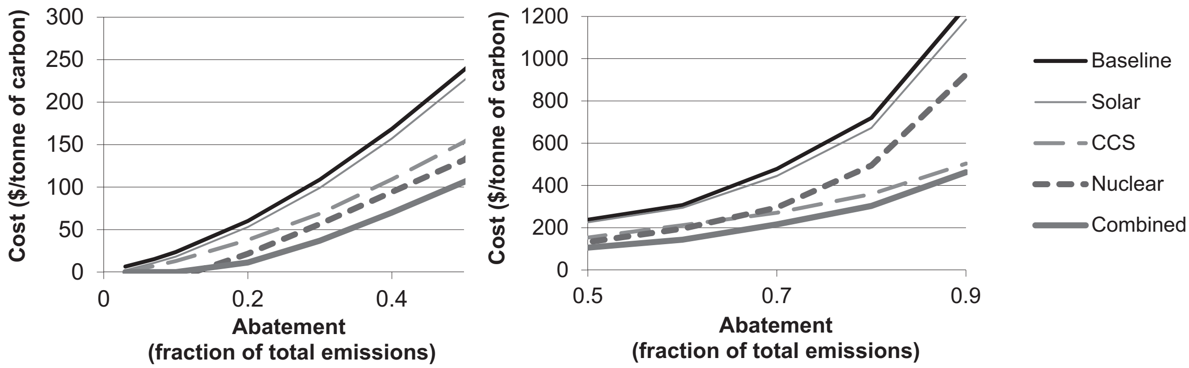

Figure S6.1 Representative MACs defining the cost of reducing the carbon emissions by an additional tonne. The two plots display the impact of technology projects on the baseline MAC for different ranges of abatement levels.

Appendix S7. Pivot Parameter Values for Individual Technology Projects

Technology	Project	Pivot Parameter
Solar	*Organic Solar Cells*	0.050
		0.022
	Inorganic Solar Cells	0.022
	3rd Generation Technologies	0.050
Carbon Capture and Storage	*Pre-comb. Carbon Capture*	0.346
	Chemical Looping	0.380
	Post-comb. Carbon Capture	0.319
Nuclear	*Light Water Reactors*	0.325
	High Temperature Reactors	0.327
		0.111
	Fast Burner Reactors	0.332
		0.115

Table S7.1 Pivot parameter values for individual projects. Multiple parameter values for a project imply that values may differ based on the level of success.

Let $\mathcal{S} = \cup_i \mathcal{S}_i$ refer to some given combination of successful technology projects, where $\mathcal{S}_i$ denotes the set of successful projects in technology i, $i = CCS, nuclear, solar$. The process for deriving the values of α_i and $h(\boldsymbol{\alpha})$ for any given set $\mathcal{S}$ was as follows. First, a project pivot parameter, denoted by α_{ij} was estimated using the generated MACs for each individual project as listed in the table above. Second, we make the assumption that, within any technology i, only the best project (the one with the greatest impact on the MAC) will impact the economy. Therefore, we define α_i as $\alpha_i = \max_j \{\alpha_{ij} : j \in \mathcal{S}_i\}$. Finally, for every combination of possible technological outcomes as represented by the three α_i's for the three technologies, a shift parameter $h(\boldsymbol{\alpha})$ was estimated numerically. For these values please contact the authors.

Note that the combined solar/nuclear parameter α_2 is calculated as $\alpha_2 = 1 - (1 - \alpha_{nuclear})(1 - \alpha_{solar})$.

Appendix S8. Proofs of Analytical Results

LEMMA 1 **(Convexity of equation** (18)**)**. *The revised output equation* (18) *can be expressed as a convex inequality constraint.*

Proof: Solak and Baker (2012) show that equation (11) in DICE can be expressed as

$$y_t - \frac{1 - c_D(\mu_t)}{D_D(\tau_t)} y_t^g \leq 0 \tag{23}$$

and that the left hand side of this constraint is convex in the decision variables for the range of parameter values used in DICE. This implies that the function is concave in the numerator $1 - c_D(\mu_t)$. Let scalar function $\ell : \mathbb{R} \to \mathbb{R}$ be defined such that

$$\ell(r) = -\frac{r}{D_D(\tau_t)} y_t^g \tag{24}$$

Hence, equation (18) can be expressed as $y_t + \ell(\varrho(\mu_t, \alpha_1, \alpha_2)) \leq 0$, where

$$\varrho(\mu_t, \alpha_1, \alpha_2) = [1 - ((1 - 0.8\alpha_1 - 0.92\alpha_2)c_D(\mu_t) - (0.02 - 0.06\alpha_1 + 0.14\alpha_2)c_D(0.5)\,\mu_t)] \tag{25}$$

Hence for the convexity of (18), it suffices to show that $\ell(\varrho(\mu_t, \alpha_1, \alpha_2))$, i.e. the composition of ℓ and ϱ is convex in the decision variables $\mu_t, \alpha_1, \alpha_2$.

Note that composition of a function with a scalar convex function is convex if the function is concave and the extended-value extension of the scalar function is nonincreasing. Given that ℓ is nonincreasing, we need to show that $\varrho(\mu_t, \alpha_1, \alpha_2)$ is concave. This can be shown by computing the Hessian of the function, and noting that the Hessian is negative semidefinite, which we skip the details for. It follows that (18) has an equivalent convex representation. □

THEOREM 1 **(Convexity of the integrated R&D and abatement policy optimization model)**. *The stochastic programming formulation* (19)-(22) *for the integrated R&D and abatement policy optimization model is convex with respect to all decision variables.*

Proof: The result follows from the proof of convexity for the deterministic DICE model by Solak and Baker (2012), Lemma 1, and the linearity of constraints (16), (21)-(22), and (36)-(38). □

PROPOSITION 1 **(Sufficiency of nonanticipativity in $\boldsymbol{\Upsilon}$, $\boldsymbol{k}$, and $\boldsymbol{u}$)**. *Let Υ_i^ω, k_t^ω, u_t^ω, and $\mathbf{x}_t^\omega$ represent the optimal decision variable values for scenarios $\omega \in \Omega$ in the integrated R&D and abatement policy optimization model, where $\mathbf{x}_t^\omega$ is the vector of all other variables. For any $\omega, \omega' \in \Omega$, if $\Upsilon_i^\omega = \Upsilon_i^{\omega'}$, $k_t^\omega = k_t^{\omega'}$, and $u_t^\omega = u_t^{\omega'}$, then there exists an optimal solution where $\mathbf{x}_t^\omega = \mathbf{x}_t^{\omega'}$.*

Proof: The result can be established by analyzing the implied relationships in formulation (6)-(10). We first note that the representative constraints (10) involve the following three constraints:

$$m_t^a = e_t + 0.811 m_{t-1}^a + 0.097 m_{t-1}^u \qquad \forall t \tag{26}$$

$$f_t = 3.8 \log\{m_t^a + m_{t+1}^a / 1192.8\} \qquad \forall t \tag{27}$$

$$\tau_t = \tau_{t-1} + 0.22(f_t - 1.27\tau_{t-1} - 0.3(\tau_{t-1} - \underline{\tau}_{t-1})) \qquad \forall t \tag{28}$$

$$\underline{\tau}_t = \underline{\tau}_{t-1} + 0.05(\tau_{t-1} - \underline{\tau}_{t-1}) \qquad \forall t \tag{29}$$

where m_t^a and m_t^u are the carbon concentrations in the atmosphere and upper oceans, f_t is the total radiative forcing, and $\underline{\tau}_t$ is the ocean temperature in period t. The conditions $\Upsilon_i^\omega = \Upsilon_i^{\omega'}$, $k_t^\omega = k_t^{\omega'}$, and $u_t^\omega = u_t^{\omega'}$ have the following implications. First, given the equality $u_t^\omega = u_t^{\omega'}$ and the definition of u_t in constraint (7), we get $o_t^\omega = o_t^{\omega'}$. Similarly, $k_t^\omega = k_t^{\omega'}$ implies through constraint (9) that $l_t^\omega = l_t^{\omega'}$. Moreover, due to the equality of variables o_t, l_t, and Υ_i in constraint (16) for scenarios ω and ω', we note that the condition $y_t^\omega = y_t^{\omega'}$ must also hold. The last relationship, along with the condition $k_t^\omega = k_t^{\omega'}$ requires that the following must hold for scenarios ω and ω':

$$\frac{1 - P_t^{1-\theta}(\mu_t^{\omega'})^\theta B_t}{1 - P_t^{1-\theta}(\mu_t^{\omega})^\theta B_t} = \frac{1 + \pi(\tau_t^{\omega'})^2}{1 + \pi(\tau_t^{\omega})^2} \tag{30}$$

Clearly, this condition will be satisfied when $\mu_t^\omega = \mu_t^{\omega'}$ and $\tau_t^\omega = \tau_t^{\omega'}$, implying the equalities $e_t^\omega = e_t^{\omega'}$ due to constraint (13), and $\underline{\tau}_t^\omega = \underline{\tau}_t^{\omega'}$ due to constraint (29). Based on this, the relationship in (28) requires that $f_t^\omega = f_t^{\omega'}$, and in turn $m_t^{a,\omega} = m_t^{a,\omega'}$ due to constraint (27). Finally, equality of values for variables e_t and m_t^a in constraint (26) results in the condition $m_t^{u,\omega} = m_t^{u,\omega'}$. Hence, it follows that there exists an optimal solution where all variables that are not explicitly included in the nonanticipativity constraints are also equal for ω and ω'. $\square$

Appendix S9. Reduced Form R&D Model

For the reduced form R&D model, we use the simplistic model of Baker and Solak (2011), where the authors reduce the economy into two periods and a single equation. A general representation of this model is as follows:

$$\min_{x_{ijk}:\forall i,j,k} \quad E_{\boldsymbol{\alpha},Z}\left[\min_{\mu}\left[\Phi\left(c_R\left(\mu\right),\boldsymbol{\alpha}\right)+ZD_R\left(\mu\right)\right]\right] \tag{31}$$

$$\text{s.t.} \quad \sum_i\sum_j\sum_k f_{ijk}x_{ijk} \leq \mathcal{B} \tag{32}$$

$$\sum_k x_{ijk} \leq 1 \qquad \forall i,j \tag{33}$$

$$0 \leq \mu \leq 1 \tag{34}$$

$$x_{ijk} \in \{0,1\} \qquad \forall i,j,k \tag{35}$$

The reduced form model determines the abatement level μ and binary technology selection decisions x_{ijk} that minimize the expectation of the sum of abatement costs $\Phi\left(c_R\left(\mu\right),\boldsymbol{\alpha}\right)$ and damage costs $D_R(\mu)$. In this objective function representation, $c_R\left(\mu\right) = b_0\mu^{b_1}$ denotes the baseline abatement cost function used in the reduced-form model, where b_0 and b_1 are calibrated parameters. The damage cost function in the reduced-form model is defined as $D_R(\mu) = M_0(Q - M_1\mu)^2$, where Q, M_0, and M_1 correspond to specific parameter values. The technology selection decisions are made in the first period and abatement is performed in the second period after realization of the uncertain parameters, which consist of the technical change indicators $\boldsymbol{\alpha}$ and the magnitude of climate change damages, i.e. Z. The probability distributions over the parameters $\boldsymbol{\alpha}$ and thus $h\left(\boldsymbol{\alpha}\right)$ depend on the R&D projects that are chosen, while the uncertainty around the magnitude Z of climate change damages is exogenous. The indices i, j and k represent the technology (CCS, nuclear, and solar), the specific project for a technology and the level of investment, respectively. The binary decision variables x_{ijk} equal 0 if there is no investment at funding level k in project j of technology i, and 1 otherwise. The other decision variable is abatement $\mu \in [0,1]$, i.e. the fraction of emissions reduced below a business-as-usual level. The investment decisions are constrained by the R&D budget $\mathcal{B}$, and by the fact that a project can be invested in only at one level, where f_{ijk} is the NPV of funding level k for project j of technology i, as given in the third column of the tables in Appendix S3.

Appendix S10. Returns Functions for the Solar-Nuclear Technology Category

Budg.($mil)	77	346	423	539	925	1967	3628	4014	4342	8975	20171	Prob.
	0	0	0	0	0	0	0	0	0	0	0	0.087
	0.022	0	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.089
	0.022	0	0.022	0.022	0.022	0.327	0.327	0.327	0.327	0.327	0.327	0.064
	0.022	0	0.022	0.022	0.022	0.131	0.131	0.131	0.131	0.131	0.131	0.044
	0.022	0	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.039
	0.022	0.325	0.325	0.325	0.325	0.325	0.325	0.325	0.325	0.325	0.325	0.157
	0	0.325	0.325	0.325	0.325	0.325	0.327	0.327	0.327	0.327	0.327	0.081
	0	0.325	0.325	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.041
α_2	0	0.325	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.124
	0	0.325	0.34	0.34	0.34	0.342	0.342	0.342	0.342	0.342	0.342	0.067
	0.022	0.325	0.325	0.325	0.325	0.325	0.325	0.325	0.325	0.325	0.361	0.01
	0.022	0	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.134	0.134	0.039
	0	0	0	0	0	0.111	0.111	0.111	0.111	0.342	0.342	0.023
	0	0	0	0	0	0.342	0.342	0.342	0.342	0.342	0.342	0.023
	0	0	0	0	0	0.327	0.342	0.342	0.342	0.342	0.342	0.025
	0	0	0	0	0	0	0.327	0.361	0.361	0.361	0.361	0.028
	0	0	0	0	0	0	0	0	0.342	0.115	0.115	0.037
	0	0	0	0	0	0.325	0.325	0.022	0.34	0.34	0.34	0.022

Table S10.1 Piecewise linear returns functions for solar-nuclear, where the central columns show values of α_2 for discrete levels of investment. Each row, which corresponds to a realization of the function $\mathcal{A}_2$, is associated with a probability given in the far right column.

Appendix S11. Representation of Stochastic Returns Functions

The stochastic returns functions in the integrated R&D and abatement policy optimization model are represented through a piecewise linear structure. In order to include this representation in the optimization framework, in addition to defining α_i^ω as variables in the model, we define new variables $\lambda_i^{\omega n} \geq 0$ for $i = 1, 2$; $\omega \in \Omega$; and $n = 0, \ldots, N_i$ where N_i is the number of vertices or budgets used to represent the returns functions for technology category i. We then include the following constraints in our formulation:

$$\Upsilon_i^\omega = \sum_{n=1}^{N_i} v_i^n \lambda_i^{\omega n} \qquad \forall i, \omega \tag{36}$$

$$\alpha_i^\omega = \sum_{n=1}^{N_i} \hat{\alpha}_i^\omega(n) \lambda_i^{\omega n} \qquad \forall i, \omega \tag{37}$$

$$\sum_{n=0}^{N_i} \lambda_i^{\omega n} = 1 \qquad \forall i, \omega \tag{38}$$

where v_i^n is the budget value for the nth vertex. These values correspond to the budgets in the top rows of Table 3 and Appendix S8. The stochastic parameter $\hat{\alpha}_i^\omega(n)$ in these constraints is the value of the return parameter α_i^ω at the nth vertex of the return function. Note that we must require that at most two adjacent $\lambda_i^{\omega n}$ can be nonzero for each i and ω to ensure that corresponding values of Υ_i^ω and α_i^ω lie on one of the straight line segments of the returns function. However, this condition is satisfied regardless due to the result in Appendix S5 that our integrated R&D and abatement policy optimization model is convex.

Appendix S12. Description of the Solution Procedure

Our solution approach to the integrated R&D and abatement policy optimization model involves a Lagrangian decomposition scheme. Note that model (19)-(22) is linked in scenarios through the nonanticipativity constraints (21)-(22). By subjecting these conditions to Lagrangian relaxation, we form the following Lagrangian

$$L(\mathbf{x},\boldsymbol{\Upsilon},\boldsymbol{k},\boldsymbol{u}) = \sum_{\omega\in\Omega} p^{\omega}\sum_{t} R_t u_t^{\omega} + \sum_{\omega\in\Omega}\sum_{i}\phi_i^{\omega}\left(\sum_{\omega'\in\Omega} p^{\omega'}\Upsilon_i^{\omega'} - \Upsilon_i^{\omega}\right) + \sum_{\omega\in\Omega}\sum_{t\leq 5}\zeta_t^{\omega}\left(\sum_{\omega'\in\Omega} p^{\omega'}k_t^{\omega'} - k_t^{\omega}\right) + \sum_{\omega\in\Omega}\sum_{t\leq 5}\eta_t^{\omega}\left(\sum_{\omega'\in\Omega} p^{\omega'}u_t^{\omega'} - u_t^{\omega}\right) \tag{39}$$

where ϕ_i^{ω}, ζ_t^{ω}, η_t^{ω} are the Lagrange multipliers. With a slight abuse of notation, we let $\mathbf{x}$ above denote all variables other than $\boldsymbol{\Upsilon}, \boldsymbol{k}$, and $\boldsymbol{u}$. A major advantage of the described formulation of the nonanticipativity constraints is that when they are relaxed, the Lagrangian (39) can be decomposed by scenarios for given dual vectors ϕ, ζ, and η. Hence, the resulting Lagrangian can be expressed as

$$L(\mathbf{x},\boldsymbol{\Upsilon},\boldsymbol{k},\boldsymbol{u}) = \sum_{\omega\in\Omega} L_{\omega}(\mathbf{x}^{\omega},\boldsymbol{\Upsilon}^{\omega},\boldsymbol{k}^{\omega},\boldsymbol{u}^{\omega}) \tag{40}$$

The corresponding Lagrangian dual problem for problem (19)-(22) is then

$$\min_{\boldsymbol{\phi},\boldsymbol{\zeta},\boldsymbol{\eta}}\{\mathcal{Z}(\boldsymbol{\phi},\boldsymbol{\zeta},\boldsymbol{\eta}) = \max\{\sum_{\omega\in\Omega} L_{\omega}(\mathbf{x}^{\omega},\boldsymbol{\Upsilon}^{\omega},\boldsymbol{k}^{\omega},\boldsymbol{u}^{\omega}) : (20)\} \tag{41}$$

Problem (41) is a nonsmooth convex minimization problem, and can be solved by subgradient optimization methods (Hiriart-Urruty and Lemarechal 1993). At each iteration of these methods, the solution of $\mathcal{Z}(\boldsymbol{\phi},\boldsymbol{\zeta},\boldsymbol{\eta})$ is required to obtain a subgradient. We note that $\mathcal{Z}(\boldsymbol{\phi},\boldsymbol{\zeta},\boldsymbol{\eta})$ is separable, and reduces to solving $|\Omega|$ problems of manageable size, each of which corresponds to a single scenario. Components of the subgradient vector Γ are then given by $\sum_{\omega'\in\Omega} p^{\omega'}\Upsilon_i^{\omega} - \Upsilon_i^{\omega}$, $\sum_{\omega'\in\Omega} p^{\omega'}k_t^{\omega'} - k_t^{\omega}$, and $\sum_{\omega'\in\Omega} p^{\omega'}u_t^{\omega'} - u_t^{\omega}$ where Υ_i^{ω}, k_t^{ω} and u_t^{ω} are the corresponding optimal solutions to the scenario subproblems.

We let Γ^j represent the subgradient at iteration j, and propose a modified subgradient algorithm consisting of a combined step size rule. More specifically, we use a weighted combination of the subgradients from previous iterations in updating the dual variables, such that:

$$\hat{\Gamma}^j = \delta_0\Gamma^j + \delta_1\Gamma^{j-1} + \delta_2\Gamma^{j-2} \tag{42}$$

where the δ terms represent weights with $\delta_0 + \delta_1 + \delta_2 = 1$. Based on an experimental analysis of convergence rates, as it is the case for most subgradient algorithm implementations, we have determined that the best choices for these weights for the given problem are $\delta_0 = 0.7$, $\delta_1 = \delta_2 = 0.15$.

Multiplier updates are then performed using the following step size rule:

$$\phi^{j+1} = \phi^j - \frac{\varphi(\bar{L}^j - \underline{L}^j)}{||\Gamma^j||}\hat{\Gamma}^j, \quad \zeta^{j+1} = \zeta^j - \frac{\varphi(\bar{L}^j - \underline{L}^j)}{||\Gamma^j||}\hat{\Gamma}^j, \quad \eta^{j+1} = \eta^j - \frac{\varphi(\bar{L}^j - \underline{L}^j)}{||\Gamma^j||}\hat{\Gamma}^j$$

where φ, $\varphi < 2$, is a constant that can be modified during the algorithm, while $\bar{L}^j$ and $\underline{L}^j$ are upper and lower bounds on the Lagrangian at iteration j, respectively. The values to be used for φ were again determined through experimental analysis. Note that any Lagrangian dual solution is an upperbound for the original problem, which can be used in evaluating the value of a given feasible solution.

Despite the improvements in convergence rates through the parameter settings above, the subgradient algorithm implementation is still not efficient enough for quick evaluations of the large number of policy environments and input configurations that we have considered as part of our analysis in this paper. However, further improvement of the solution procedure is possible by establishing the following result about the structure of the optimal investment decisions for the given piecewise linear returns functions.

PROPOSITION 2. *If $\lambda_i^{n\omega,*}$ represent the optimal values for variables $\lambda_i^{n\omega}$, then $\lambda_i^{n\omega,*} \in \{0,1\}$ for all n, i and ω, i.e. the optimal investment decision for each technology category i corresponds to a vertex value in the corresponding piecewise linear returns function.*

Proof: The result follows from a marginal analysis. Consider equation (16) as defined for each scenario $\omega \in \Omega$. Given that maximization of the utility in each period implies the maximization of the net output y_t^ω for that period, it is optimal to increase investment by Δ_i units as long as $E_\omega[\Delta_i^{y,\omega}] \geq \kappa\frac{\Delta_i}{5}$, where $\Delta_i^{y,\omega}$ is the change in the net output value of scenario ω for a Δ_i unit increase in investment for technology category i.

By definition, the marginal returns and costs are the same in the range $\Upsilon_i \in [v_i^n, v_i^{n+1}]$ for all n due to the linear relationships between investment levels and α_i^ω. Suppose for some i, n and ω, $0 < \lambda_i^{n\omega,*} < 1$, i.e. the optimal investment is not a vertex value implying that $v_i^n < \bar{v}_i < v_i^{n+1}$, where $\Upsilon_i^* = \bar{v}_i$. Assuming without loss of generality that the expected returns are increasing between vertices n and $n+1$, the optimality conditions imply that $E_\omega[\Delta_i^{y,\omega}] \geq \kappa\frac{\Delta_i}{5}$ in the range $\Upsilon_i \in [v_i^n, \bar{v}_i]$. On the other hand, this should also hold for the range $\Upsilon_i \in [\bar{v}_i, v_i^{n+1}]$ due to the constancy of marginal returns between vertices n and $n+1$. Hence, it is possible to increase social utility by increasing the investment level to the value at vertex $n+1$, which is a contradiction implying that $\bar{v}_i$ can not be optimal. This would require $\lambda_i^{n\omega,*} \in \{0,1\}$ for all n, i and ω.$\square$

Hence, it is possible to implement an implicit enumeration procedure for the investment levels at the vertices of the piecewise linear returns functions and only solve for the optimal abatement policy at those implicitly enumerated investments levels. Implementation of this procedure improves the overall solution time as the subgradient iterations are only implemented over the variables u and k for given investment levels.

Appendix S13. Allocation of Total Investment under Different Optimal Investment Values

Investments ($ million)									Total Inv ($bil)
CCS			Nuclear			Solar			
Pre C	Chem L	Post C	LWR	HTR	FR	Org	Inorg	3rd G	
386	56	519	346	3089	15443	830	77	386	21.132
386	56	519	346	3089	0	830	77	0	5.303
154	56	519	346	3089	0	830	77	0	5.071
154	56	519	346	1544	0	0	77	0	2.696

Table S13.1 Allocation of total investment under different optimal investment values.

Appendix S14. R&D and Riskiness of Outcomes

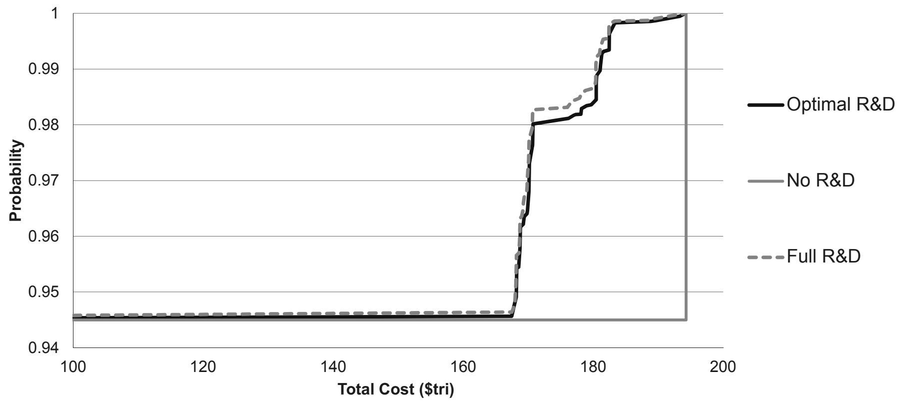

Figure S14.1 Cumulative distribution function comparing different R&D policies in the Risk 3 DICE Optimal case.

We consider how investment into R&D impacts the riskiness of the policy outcomes. Figure S14.1 shows part of three cumulative distribution functions (CDFs). The CDFs are for DICE Optimal under high risk (Risk 3), comparing no R&D, optimal R&D, and full R&D. The horizontal axis represents the present value of total costs. Each point on the graph represents the probability that total costs are less than or equal to the value on the horizontal axis. For example, the probability that the total cost is less than $170 trillion, given an optimal investment in R&D, is about 0.98. We only show the far right of the graph, since there is no visual difference between the three cases on the rest of the graph. Note that society would prefer to be as far left as possible on this graph, and so a higher line is preferred to a lower line. There is a 5.5% chance that high damages (about 20 times higher than the mean) realize in the Risk 3 case. If there is no R&D, then damages in this case will be equal to $194 trillion. With full or optimal R&D however, damages may be limited, with only about a 2% chance that damages are greater than $170 trillion. Thus, *R&D provides risk reduction* (visualized as the area between the darker and the lighter solid curves).

References

Anadon, L., V. Bosetti, M. Bunn, M. Catenacci, A. Lee. 2011a. Report of international workshop on RD&D to enhance the role of nuclear energy in meeting climate and energy challenges. Tech. rep., Harvard Kennedy School.

Anadon, L., M. Bunn, G. Chan, M. Chan, C. Jones, R. Kempener, A. Lee, N. Logar, V. Narayanamurti. 2011b. Transforming U.S. energy innovation. Tech. rep., Harvard Kennedy School.

Baker, E. 2009. Uncertainty and learning in climate change. *Journal of Public Economic Theory* **11** 721 – 747.

Baker, E., H. Chon, J. Keisler. 2008. Nuclear Power. Working Paper.

Baker, E., H. Chon, J. Keisler. 2009a. Advanced solar R&D. *Energy Economics* **31** S37 – S49.

Baker, E., H. Chon, J. Keisler. 2009b. Carbon capture and storage. *Clim. Change* **96(3)** 379.

Baker, E., Y. Peng. 2012. The value of better information on technology R&D programs in response to climate change. *Environmental Modeling and Assessment* **17(1)** 107–121.

Baker, E., E. Shittu. 2008. Uncertainty and endogenous technical change in climate policy models. *Energy Economics* **30**.

Baker, E., S. Solak. 2011. Climate change and optimal energy technology R&D policy. *European Journal of Operational Research* **213** 442–454.

Blanford, G.J. 2009. R&D investment strategy for climate change: A numerical study. *Energy Economics* **31** S27–S36.

Blanford, G.J., J.P. Weyant. 2007. Optimal investment portfolios for basic R&D. Working Paper, Stanford University.

Bosetti, V., M. Catenacci, G. Fiorese, E. Verdolini. 2012. The future prospect of PV and CSP solar technologies. Working paper, Fondazione Eni Enrico Mattei.

Brenkert, A.S., S. Smith, S. Kim, H. Pitcher. 2003. Model documentation for the MiniCAM. Tech. Rep. PNNL-14337, Pacific Northwest National Laboratory.

Caroe, C.C., R. Schultz. 1999. Dual decomposition in stochastic integer programming. *OR Letters* **24** 37–45.

Chan, G., L. Anadon, M. Chan, A. Lee. 2011. Expert elicitation of cost, performance, and RD&D budgets for coal power with CCS. *Energy Procedia* **4** 2685–2692.

Clarke, L., J. Edmonds, V. Krey, R. Richels, S. Rose, M. Tavoni. 2009. International climate policy architectures. *Energy Economics* **31** s64 – s81.

Clarke, L., P. Kyle, M.A. Wise, K. Calvin, J.A. Edmonds, S.H. Kim, M. Placet, S. Smith. 2008. CO_2 emissions mitigation and technological advance. Tech. rep., Pacific NW Nat. Lab.

Curtright, A., M. Morgan, D. Keith. 2008. Expert assessments of future photovoltaic technologies. *Environmental Science & Technology* **42** 9031–9038.

Edmonds, J.A., J.F. Clarke, J.J. Dooley, S.H. Kim, S.J. Smith. 2005. Stabilization of CO_2 in a B2 world. John Weyant, Richard Tol, eds., *Special Issue, Energy Economics*.

Gore, A. 2007. Moving beyond Kyoto. New York Times, July 1.

Hiriart-Urruty, J-B., C. Lemarechal. 1993. *Convex Analysis and Min. Algorithms I*. Springer.

Hora, S. 2004. Probability judgments for continuous quantities: linear combinations and calibration. *Management Science* **50** 597 – 604.

InterAcademy Council. 2010. Climate change assessments: Review of the processes & procedures of the IPCC. Tech. rep., InterAcademy Council.

Lewis, N.S., D.G. Nocera. 2006. Powering the planet: Chemical challenges in solar energy utilization. *Proceedings of the National Academy of Sciences* **43** 15729 – 15735.

Louveaux, F.V., R. Schultz. 2003. *Handbooks in Operations Research and Management Science*, vol. 10, chap. 4. Elsevier Science, 213–266.

National Research Council. 2007. *Prospective Evaluation of Applied Energy Research and Development at DOE (Phase Two)*. The National Academies Press, Washington D.C.

Nordhaus, W.D. 1993. Rolling the DICE. *Resource and Energy Economics* **15** 27–50.

Nordhaus, W.D. 1994. *Managing the Global Commons*. MIT Press, Boston, MA.

Nordhaus, W.D. 2002. Modeling induced innovation in climate change policy. A. Grubler, N. Nakicenovic, W. D. Nordhaus, eds., *Technological Change and the Environment*. RFF and IIASA, Washington D.C. and Laxenburg, Austria, 182–209.

Nordhaus, W.D. 2008. *A Question of Balance*. Yale University Press, New Haven, CT.

Nordhaus, W.D. 2011. Designing a friendly space for technological change to slow global warming. *Energy Economics* **33** 665 – 673.

Pizer, W. A., D. Popp. 2008. Endogenizing technological change. *Energy Econ.* **30** 2754–2770.

Rao, A., E. Rubin, D. Keith, M. Morgan. 2006. Evaluation of potential cost reductions from improved amine-based CO_2 capture systems. *Energy Policy* **34** 3765 – 3772.

Solak, S., E. Baker. 2012. Convexity analysis for the DICE model. Manuscript under Review.

Stern, N. 2007. *The Economics of Climate Change*. Cambridge Univ. Press, Cambridge, MA.

Tversky, A., D. Kahneman. 1974. Judgement under uncertainty. *Science* **185** 1124–1131.