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
- \( c_D(\mu) \): 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 \( t \)
- \( G_s(\cdot) \): 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
- \( h(\alpha) \): shift effect in the marginal abatement curve due to technological success
- \( J_\psi^s(\cdot) \): representative function modeling the constraint \( \psi \) for scenario \( \omega \)
- \( k_t \): 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
- \( x_s \): generic vector representing all decision variables other than abatement decisions in stage \( s \), \( s = N, L \)
- \( x(\cdot) \): generic vector representing all decision variables other than abatement decisions
- \( y_t \): net output of goods/services in period \( t \)
- \( y^s_t \): unadjusted output in period \( t \)
- \( y_s \): vector representing net output of goods/services in stage \( s \), \( s = N, L \)
- \( \alpha_i \): pivot effect in the marginal abatement curve due to success in technology \( i \)
- \( \mu_t \): level of emissions abatement in period \( t \)
- \( \mu_s \): vector representing emissions abatement decisions in stage \( s \), \( s = N, L \)
- \( \Phi(c(\mu), \alpha) \): functional representing cost of emissions abatement after technical change
- \( \tau_t \): atmospheric temperature in period \( t \)
- \( \tau_s \): vector representing atmospheric temperature in stage \( s \), \( s = N, L \)
- \( \Upsilon_i \): vector representing investment decisions in technology category \( i \)
- \( \Upsilon(\cdot) \): vector representing investment decisions in technologies

**Parameters**
- \( A_i \): stochastic entity representing the returns function for technology category \( i \)
- \( A_t \): level of total factor productivity in period \( t \)
- \( b_\psi \): representative parameter modeling the right hand side of constraint \( \psi \) for scenario \( \omega \)
- \( b_s \): representative vector modeling the right hand sides of constraints for stage \( s \), \( s = N, L \)
- \( B \): 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 \( t \)
\( p^\omega \): probability of scenario \( \omega \)
\( P_t \): 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
\( \alpha_{ij} \): calculated pivot effect in the marginal abatement curve due to success in project \( j \) in technology \( i \)
\( \beta \): elasticity of marginal utility of consumption
\( \gamma \): elasticity of output with respect to capital
\( \theta \): cost function exponent set to 2.8 in DICE
\( \kappa \): opportunity cost parameter
\( \pi \): stochastic parameter modeling the magnitude of climate damages
\( \sigma \): rate of depreciation of capital
Appendix S3. Summary of Expert Elicitation Results

<table>
<thead>
<tr>
<th>Technology</th>
<th>Project</th>
<th>NPV of Funding (000,000)</th>
<th>Probability of success</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carbon Capture and Storage (CCS)</td>
<td>Pre-combustion</td>
<td>$39</td>
<td>2.7%</td>
</tr>
<tr>
<td></td>
<td>Carbon Capture (Pre C)</td>
<td>$154</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>$386</td>
<td>22.3%</td>
</tr>
<tr>
<td></td>
<td>Chemical Looping</td>
<td>$19</td>
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</tr>
<tr>
<td></td>
<td>(Chem L)</td>
<td>$38</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>$56</td>
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<td></td>
<td>Post-combustion</td>
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<td>59.0%</td>
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<td>Carbon Capture (Post C)</td>
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<tr>
<td></td>
<td></td>
<td>$519</td>
<td>78.5%</td>
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Table S3.1  Summary of expert elicitation results for the CCS technology (Baker et al. 2009b).

<table>
<thead>
<tr>
<th>Technology</th>
<th>Project</th>
<th>NPV of Funding (000,000)</th>
<th>Probability of success</th>
</tr>
</thead>
<tbody>
<tr>
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<tr>
<td></td>
<td></td>
<td>$260</td>
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<tr>
<td></td>
<td></td>
<td>$346</td>
<td>60.0%</td>
</tr>
<tr>
<td></td>
<td>High Temperature Reactors (HTR)</td>
<td>$722</td>
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<tr>
<td></td>
<td></td>
<td>$1,544</td>
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<tr>
<td></td>
<td></td>
<td>$3,089</td>
<td>40.3%</td>
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<tr>
<td></td>
<td>Fast Burner Reactors (FR)</td>
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<tr>
<td></td>
<td></td>
<td>$4,433</td>
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<td></td>
<td></td>
<td>$15,443</td>
<td>60.0%</td>
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</tbody>
</table>

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

<table>
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<th>Technology</th>
<th>Project</th>
<th>NPV of Funding (000,000)</th>
<th>Probability of success</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solar</td>
<td>Organic Solar Cells (Org)</td>
<td>$116</td>
<td>0.0%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$830</td>
<td>3.9%</td>
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<tr>
<td></td>
<td>Inorganic Solar Cells (Inorg)</td>
<td>$39</td>
<td>26.7%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$77</td>
<td>44.3%</td>
</tr>
<tr>
<td></td>
<td>3rd Generation</td>
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<td></td>
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<tr>
<td></td>
<td>Technologies (3rd G)</td>
<td>$386</td>
<td>2.0%</td>
</tr>
</tbody>
</table>

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 \( c_D(\mu_t) = P_t^{1-\theta} B_t \mu_t^0 \) where \( \theta \) 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

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

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 $S = \cup_i S_i$ refer to some given combination of successful technology projects, where $S_i$ denotes the set of successful projects in technology $i$, $i = CCS, nuclear, solar$. The process for deriving the values of $\alpha_i$ and $h(\alpha)$ for any given set $S$ was as follows. First, a project pivot parameter, denoted by $\alpha_{ij}$ 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 $\alpha_i$ as $\alpha_i = \max_j \{\alpha_{ij} : j \in S_i\}$. Finally, for every combination of possible technological outcomes as represented by the three $\alpha_i$’s for the three technologies, a shift parameter $h(\alpha)$ was estimated numerically. For these values please contact the authors.

Note that the combined solar/nuclear parameter $\alpha_2$ 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

\[ y_t - \frac{1 - c_D(\mu_t)}{D_D(\tau_t)} y^g_t \leq 0 \]  

(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 \( \ell : \mathbb{R} \rightarrow \mathbb{R} \) be defined such that

\[ \ell(r) = -\frac{r}{D_D(\tau_t)} y^g_t \]  

(24)

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

\[ q(\mu_t, \alpha_1, \alpha_2) = [1 - ((1 - 0.8\alpha_1 - 0.92\alpha_2)c_D(\mu_t) - (0.02 - 0.06\alpha_1 + 0.14\alpha_2)c_D(0.5)\mu_t)] \]  

(25)

Hence for the convexity of (18), it suffices to show that \( \ell(q(\mu_t, \alpha_1, \alpha_2)) \), i.e. the composition of \( \ell \) and \( q \) 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 \( \ell \) is nonincreasing, we need to show that \( q(\mu_t, \alpha_1, \alpha_2) \) 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 \( \Upsilon, k, \) and \( u \)).** Let \( \Upsilon_i^\omega, k_i^\omega, u_i^\omega \), and \( x_i^\omega \) represent the optimal decision variable values for scenarios \( \omega \in \Omega \) in the integrated R&D and abatement policy optimization model, where \( x_i^\omega \) is the vector of all other variables. For any \( \omega, \omega' \in \Omega \), if \( \Upsilon_i^\omega = \Upsilon_i^{\omega'}, k_i^\omega = k_i^{\omega'} \), and \( u_i^\omega = u_i^{\omega'} \), then there exists an optimal solution where \( x_i^\omega = x_i^{\omega'} \).
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:

\[ m_t^\omega = e_t + 0.811m_{t-1}^\omega + 0.097m_{t-1}^u \quad \forall t \]  \hspace{1cm} (26)
\[ f_t = 3.8\log\left\{ m_t^\omega + m_{t+1}^\omega / 1192.8 \right\} \quad \forall t \]  \hspace{1cm} (27)
\[ \tau_t = \tau_{t-1} + 0.22(f_t - 1.27\tau_{t-1} - 0.3(\tau_{t-1} - \tau_{t-1})) \quad \forall t \]  \hspace{1cm} (28)
\[ \tau_t = \tau_{t-1} + 0.05(\tau_{t-1} - \tau_{t-1}) \quad \forall t \]  \hspace{1cm} (29)

where \( m_t^\omega \) and \( m_t^u \) are the carbon concentrations in the atmosphere and upper oceans, \( f_t \) is the total radiative forcing, and \( \tau_t \) 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 \( \Upsilon_t \) in constraint (16) for scenarios \( \omega \) and \( \omega' \), 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 \( \omega \) and \( \omega' \):

\[
\frac{1 - P_t^{1-\theta}(\mu_t^\omega')^{\theta}B_t}{1 - P_t^{1-\theta}(\mu_t^\omega)^{\theta}B_t} = \frac{1 + \pi(\tau_t^\omega')^2}{1 + \pi(\tau_t^\omega)^2}
\]  \hspace{1cm} (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 \( \tau_t^\omega = \tau_t^\omega' \) due to constraint (29). Based on this, the relationship in (28) requires that \( f_t^\omega = f_t^\omega' \), and in turn \( m_t^\omega = m_t^\omega' \) due to constraint (27). Finally, equality of values for variables \( e_t \) and \( m_t^\omega \) in constraint (26) results in the condition \( m_t^\omega = m_t^\omega' \). 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 \( \omega \) and \( \omega' \). \( \square \)
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:

\[
\min_{x_{ijk}, x, \mu, \alpha, Z} E_{\alpha, Z} \left[ \min_{\mu} \left[ \Phi (c_R (\mu), \alpha) + Z D_R (\mu) \right] \right] \\
\text{s.t.} \quad \sum_i \sum_j \sum_k f_{ijk} x_{ijk} \leq B \\
\sum_k x_{ijk} \leq 1 \quad \forall i, j \\
0 \leq \mu \leq 1 \\
x_{ijk} \in \{0, 1\} \quad \forall i, j, k
\] (31) (32) (33) (34) (35)

The reduced form model determines the abatement level \( \mu \) and binary technology selection decisions \( x_{ijk} \) that minimize the expectation of the sum of abatement costs \( \Phi (c_R (\mu), \alpha) \) and damage costs \( D_R (\mu) \). In this objective function representation, \( c_R (\mu) = b_0 \mu b_1 \) 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 \( \alpha \) and the magnitude of climate change damages, i.e. \( Z \). The probability distributions over the parameters \( \alpha \) and thus \( h (\alpha) \) 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 \( B \), 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

<table>
<thead>
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<th>Budg.($mil)</th>
<th>77</th>
<th>346</th>
<th>423</th>
<th>539</th>
<th>925</th>
<th>1967</th>
<th>3628</th>
<th>4014</th>
<th>4342</th>
<th>8975</th>
<th>20171</th>
<th>Prob.</th>
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</thead>
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<td>0</td>
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<td>0.02</td>
<td>0.02</td>
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<td>0.02</td>
<td>0.022</td>
<td>0.087</td>
</tr>
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Table S10.1  Piecewise linear returns functions for solar-nuclear, where the central columns show values of $\alpha_2$ 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 $\alpha_{i,\omega}^\omega$ as variables in the model, we define new variables $\lambda_{i,\omega}^\omega n \geq 0$ 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:

$$\Upsilon_{i,\omega}^\omega = \sum_{n=1}^{N_i} v_i^n \lambda_{i,\omega}^\omega n \quad \forall i, \omega \tag{36}$$

$$\alpha_{i,\omega}^\omega = \sum_{n=1}^{N_i} \hat{\alpha}_{i,\omega}(n) \lambda_{i,\omega}^\omega n \quad \forall i, \omega \tag{37}$$

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

where $v_i^n$ is the budget value for the $n$th 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 $\alpha_{i,\omega}^\omega$ at the $n$th vertex of the return function. Note that we must require that at most two adjacent $\lambda_{i,\omega}^\omega n$ can be nonzero for each $i$ and $\omega$ to ensure that corresponding values of $\Upsilon_{i,\omega}^\omega$ and $\alpha_{i,\omega}^\omega$ 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

$$L(x, \mathbf{Y}, k, u) = \sum_{\omega \in \Omega} p^\omega \sum_t R_t u_t^\omega + \sum_{\omega, t} \phi_i^\omega \left( \sum_{\omega' \in \Omega} p^{\omega'} \mathbf{Y}_i^{\omega'} - \mathbf{Y}_i^\omega \right)$$

$$+ \sum_{\omega, t \leq 5} \zeta_t^\omega \left( \sum_{\omega' \in \Omega} p^{\omega'} k_t^{\omega'} - k_t^\omega \right) + \sum_{\omega, t \leq 5} \eta_t^\omega \left( \sum_{\omega' \in \Omega} p^{\omega'} u_t^{\omega'} - u_t^\omega \right)$$ (39)

where $\phi_i^\omega$, $\zeta_t^\omega$, $\eta_t^\omega$ are the Lagrange multipliers. With a slight abuse of notation, we let $x$ above denote all variables other than $\mathbf{Y}$, $k$, and $u$. 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 $\phi$, $\zeta$, and $\eta$. Hence, the resulting Lagrangian can be expressed as

$$L(x, \mathbf{Y}, k, u) = \sum_{\omega \in \Omega} L_\omega(x^\omega, \mathbf{Y}_i^\omega, k_t^\omega, u_t^\omega)$$ (40)

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

$$\min_{\phi, \zeta, \eta} \{ Z(\phi, \zeta, \eta) = \max_{\omega \in \Omega} \{ \sum_{\omega} L_\omega(x^\omega, \mathbf{Y}_i^\omega, k_t^\omega, u_t^\omega) : (20) \} \}$$ (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 $Z(\phi, \zeta, \eta)$ is required to obtain a subgradient. We note that $Z(\phi, \zeta, \eta)$ is separable, and reduces to solving $|\Omega|$ problems of manageable size, each of which corresponds to a single scenario. Components of the subgradient vector $\Gamma$ are then given by $\sum_{\omega} p^{\omega'} \mathbf{Y}_i^{\omega'} - \mathbf{Y}_i^\omega$, $\sum_{\omega} p^{\omega'} k_t^{\omega'} - k_t^\omega$, and $\sum_{\omega} p^{\omega'} u_t^{\omega'} - u_t^\omega$ where $\mathbf{Y}_i^\omega$, $k_t^\omega$, and $u_t^\omega$ are the corresponding optimal solutions to the scenario subproblems.

We let $\Gamma^j$ 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:

$$\hat{\Gamma}^j = \delta_0 \Gamma^j + \delta_1 \Gamma^{j-1} + \delta_2 \Gamma^{j-2}$$ (42)
where the $\delta$ 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:

$$
\phi^{j+1} = \phi^j - \varphi \frac{\delta_j - \delta_j}{||\Gamma^j||} \hat{\Gamma}^j, \quad \zeta^{j+1} = \zeta^j - \varphi \frac{\delta_j - \delta_j}{||\Gamma^j||} \hat{\Gamma}^j, \quad \eta^{j+1} = \eta^j - \varphi \frac{\delta_j - \delta_j}{||\Gamma^j||} \hat{\Gamma}^j
$$

where $\varphi, \varphi < 2$, is a constant that can be modified during the algorithm, while $\bar{\delta}_j$ and $\underline{\delta}_j$ are upper and lower bounds on the Lagrangian at iteration $j$, respectively. The values to be used for $\varphi$ 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 $\omega$, 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 $y_t^{\omega}$ for that period, it is optimal to increase investment by $\Delta_i$ units as long as $E_\omega[\Delta_i^{y, \omega}] \geq \kappa \frac{\Delta_i}{\delta}$, where $\Delta_i^{y, \omega}$ is the change in the net output value of scenario $\omega$ for a $\Delta_i$ 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 $\alpha_i^{\omega}$. Suppose for some $i$, $n$ and $\omega$, $0 < \lambda_i^{n, \omega,*} < 1$, 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 $E_\omega[\Delta_i^{y, \omega}] \geq \kappa \frac{\Delta_i}{\delta}$ in the range $\Upsilon_i \in [v_i^n, \bar{v}_i]$. On
the other hand, this should also hold for the range $\Upsilon_i \in [\bar{v}_i, \nu_i^{n+1}]$ 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 $\lambda_i^{n\omega, \ast} \in \{0, 1\}$ for all $n$, $i$ and $\omega$. □

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

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


