Optimal investment strategy in low-carbon energy R&D with uncertain payoff

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  - Asset price: net present cost of using the developed technology to mitigate CO\textsubscript{2} (stochastic)
  - Exercise price: avoided net present cost of mitigating CO\textsubscript{2} with a backstop technology (deterministic, reflective of CO\textsubscript{2} price)
Stochastic cost model

\[ \frac{dC}{C} = -\lambda I \, dt + \sigma \, dz \]

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
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<tbody>
<tr>
<td>$C$</td>
<td>Net present cost of CO$_2$ mitigation with modeled technology</td>
</tr>
<tr>
<td>$I$</td>
<td>Annual R&amp;D investment</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Effectiveness of R&amp;D spending</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Annual proportional standard deviation of $C$</td>
</tr>
<tr>
<td>$z$</td>
<td>Standard Brownian motion</td>
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</tbody>
</table>
Stochastic cost model

- Dashed lines are 95% prediction interval
**Stochastic cost model**

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- Final cost, measured at time $t = 7$, follows a lognormal distribution (right)
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Unlike in Monte Carlo analysis, e.g., no sample paths are generated
Solution method: continuous time SDP

- Proceed from the Bellman equation:

\[
V(C, t) = \max_I \left\{ -I \Delta t + \frac{1}{1 + \mu \Delta t} \mathbb{E}[V(C', t + \Delta t) | C, I] \right\}
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- Substitution yields the PDE:

\[ \mu V = \max_I \left\{ I \left( -\lambda C \frac{\partial V}{\partial C} - 1 \right) + \frac{1}{2} \sigma^2 C^2 \frac{\partial^2 V}{\partial C^2} + \frac{\partial V}{\partial t} \right\} \]
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3. The PDE is solved numerically using the Crank-Nicolson method in MATLAB.
R&D investment decision rule

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- Below $C_l$, the technology is already so inexpensive that further R&D is not justified.
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- Between the thresholds R&D spending at the maximum feasible rate is optimal
Estimating $\lambda$, $q$, and $\sigma$ for solar PV


Solar PV could mitigate 0.25 GtC/yr in the U.S. at 800 GW by 2050 (under assumptions of Drury et al. (2009); BAU 2050 U.S. emissions is 0.85 GtC/yr (AEO)). Assuming constant growth until 2050, a discount rate of 3%, a 30-year lifetime, deterministic learning after 2030, and a carbon price of $20/\text{tCO}_2$, avoided CO$_2$ emissions from solar PV discounted to 2030 amount to $170$ billion. If maximum yearly R&D spending $q = 400$ million, then $\lambda = 0.13$.\footnote{Drury, E., Denholm, P., and Margolis, R. The solar photovoltaics wedge: pathways for growth and potential carbon mitigation in the US. Environmental Research Letters 4 (2009) 034010 (11pp).}
Estimating $\lambda$, $q$, and $\sigma$ for solar PV

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- If maximum yearly R&D spending $q = $400 million, then $\lambda = 0.13$.

NPV analysis

The initial NPV of the investment opportunity was calculated by finding the optimal investment strategy under expected cost.
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![Graph showing initial NPV analysis](image)

- Initial Cost vs Investment value ($B)
- Time (y) vs Cost ($B)
Value of investment opportunity with stochastic cost
Comparative statics: $\sigma$ (cost volatility)

- Uncertainty adds substantial value for high initial cost but slightly lowers value for lower initial cost.
- Uncertainty renders initial investment in unprofitable projects optimal.
Comparative statics: $\lambda$ (R&D effectiveness)

- Greater effectiveness of R&D spending adds substantial value to the investment opportunity and raises the cost threshold below which initial investment is optimal.
Comparative statics: $q$ (maximum yearly R&D spending)

- Raising the maximum level of R&D investment has less effect on the value of the investment opportunity than raising $\lambda$.
- For higher $q$, $C_u$ is higher due to greater ability to drive costs down, and $C_l$ is higher due to the discount rate (since more R&D spending can be shifted to the future).
Unlike NPV analysis, optimizing R&D investment strategy under uncertainty captures the value of initial investment in negative-NPV projects, the possibility of negative learning, and the ability to update decisions as uncertainty is resolved.
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Further work will produce a decision support tool to yield insight into optimal R&D investment strategy under varying expectations on the effectiveness and risk of R&D spending.
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Questions?