Strategic technology RD&D porfolio :

What is optimal, what is feasible ?

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Introduction

Technological change is uncertain and capital intensive:

- Requiring important initial efforts in research, development and deployment (RD&D)
- Particularly risky regarding the real achievement of a technological breakthrough.

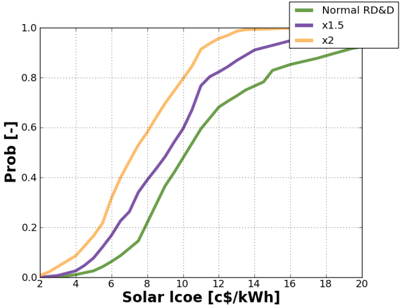
Those characteristics are exacerbated for the foreseen low-carbon technologies needed to avoid climate change.

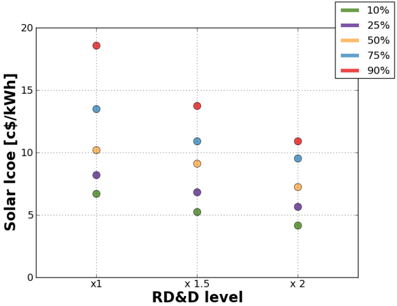
- What is the optimal RD&D profolio?

Elicitation surveys (Icarus)

Goal: Assessing the probability distribution of future costs (c)

- Global answers, not focused on a single technology
- CDF for different levels of RD&D expenditures (rd)





- rd highly impacts the distribution
- TEAM: what is the value of the different RD&D budgets ?

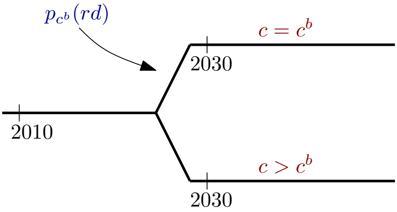
A (naive) first attempt

The probability of reaching the breakthrough cost c^b

rd	x1	x 1.5	x2
Prob($c < c^b$)	0.026	0.078	0.166

Table: Probability of having a lcoe solar less than 7 [c$/kWh]

Idea: Fit a function $p_{c^b}(rd) = \text{Prob}(c \leq c^b | rd)$



- Objective function (expected utility):

$$U \equiv u_0(x_0, rd) + p_{c^b}(rd) u_1(x_1 | c = c^b) + (1 - p_{c^b}(rd))\, u_1(x_1 | c > c^b)$$

- Limitation :
  - Arbitrary choice of c^b (depend on the IAM)
  - Difficult to handle more than one technology
  - Hard to solve (non-convex)

Learning curves

Technical change is commonly seen as a result of dedicated effort in RD&D and learning-by-doing.

- Literature pervades of evidences and estimations of factor learning curve

$$\frac{c_t}{c_0} = \left(\frac{\mathrm{rd}_t}{\mathrm{rd}_0}\right)^{-\lambda_r} \left(\frac{cum_t}{cum_0}\right)^{-\lambda_d}$$

- We cannot separate the two phenomena from the survey

$\Rightarrow$ Learning-by-researching curve with uncertain learning

$$c_t = \mathrm{LBR}(rd_t, \lambda) = c_0 \left(\frac{\mathrm{rd}_t}{\mathrm{rd}_0}\right)^{-\lambda}$$

$\Rightarrow$ Fitting a distribution for the learning parameter λ

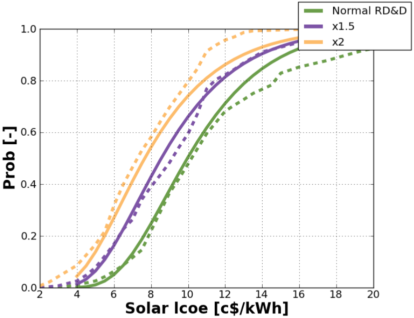
Example: fitting λ_r for solar

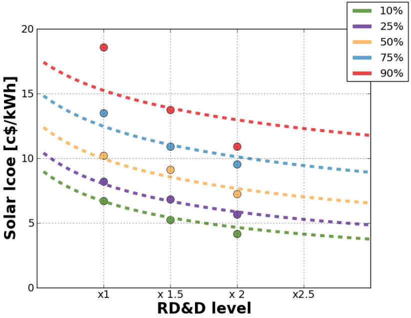
Assuming a distribution for λ_r, we fit the parameters of the distribution minimizing the error:

- e.g. for a log-Normal

$$\epsilon(\mu,\sigma) \equiv (1-\alpha) - \Phi\left(\frac{\ln(\frac{\mathsf{rd}}{\mathsf{rd}_0})/\ln(\frac{c}{c_0}) - \ln(\mu)}{\sigma}\right)$$

We tried 3 distributions : log-Normal, Weibull, Gamma



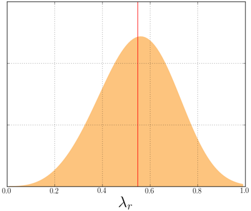


A simplified problem

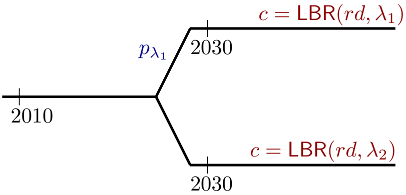
One invests rd without knowing the efficiency of its investment

quantile	0.1	0.25	0.50	0.75	0.90
	20.9	26.2	31.7	36.7	40.6

Table: CDF for the learning rate [% reduc. cost / doubling]



Ex: Discretized two-stages problem



- The probability distribution is exogenous
- Utility function:

$$U \equiv u_0(x_0, rd) + p_{\lambda_1} u_1(x_1, \text{rd}|\lambda_1) + (1 - p_{\lambda_1}) u_1(x_1, \text{rd}|\lambda_2)$$

- Easier to handle more than 1 technology

A more realistic problem

Handling multiple technologies and continuous distribution for the λ's lead to a intractable problem (curse of dimensionality).

We solve the problem using Approximate Dynamic Programming (ADP).

- The dynamic equations of the problem:

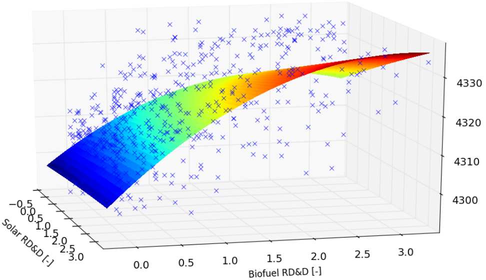
$$V_1(\mathsf{rd}, x_0, \lambda) \equiv \begin{array}{l} \max\limits_{x_1} u_1(x_1) \\ x_1 \in \mathcal{X}(x_0) \\ c_1 = \mathsf{LBR}(\mathsf{rd}, \lambda) \end{array} \qquad \Rightarrow \mathcal{V}_0(\mathsf{rd}, x_0) = \mathbb{E}[V_1(\mathsf{rd}, x_0, \lambda)]$$

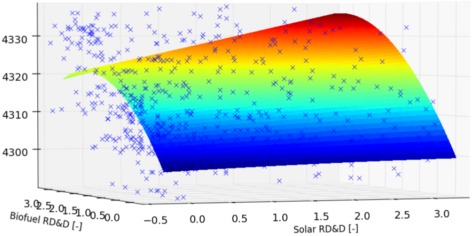
At the first stage, one needs to solve:

$$\max_{x_0, \mathsf{rd}} u_0(x_0, \mathsf{rd}) + \mathcal{V}_0(\mathsf{rd}, x_0)$$

- Assumptions made by the algorithm
  - The uncertainty on technological change does not impact the technology mix at $t = 0$ (i.e. x_0 does not change)
  - Build (and update) a surrogate model $\tilde{\mathcal{V}}_0(\mathsf{rd})$ for $\mathcal{V}_0(\mathsf{rd}, x_0)$

Illustration of $\tilde{\mathcal{V}}_0(\mathrm{rd})$





Caveat: modelling the learning after 2030

How should we limit the learning process after 2030 ?

- otherwise, it might be optimal to just wait 2030 before investing
- but restricting RD&D after 2030 is not a realistic constraint

For example in TEAM, we assume an additional learning of 20% after 2030.

Scope of the analysis

Additionaly to the usual sensitivity analysis on different climate policies, we will attempt to cover the following topics .

Limited RD&D budget

- Public money is scarce, specially today
- How evolves the optimal portfolio with constraints on governments' budgets ?

RD&D spillovers

- There are empirical evidences that knowledge spills over to other regions after a certain amount of time
- Effectiveness of an investment depends on the region's distance from the technological frontier.
- Modifies the optimal portfolio: specialization, incentive to wait,...