

How Grid Integration Costs Impact the Optimal R&D Portfolio into Electricity Supply Technologies in the Face of Climate Change

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Motivation

R&D into renewable energy makes reducing CO2 emissions cheaper and easier, but...

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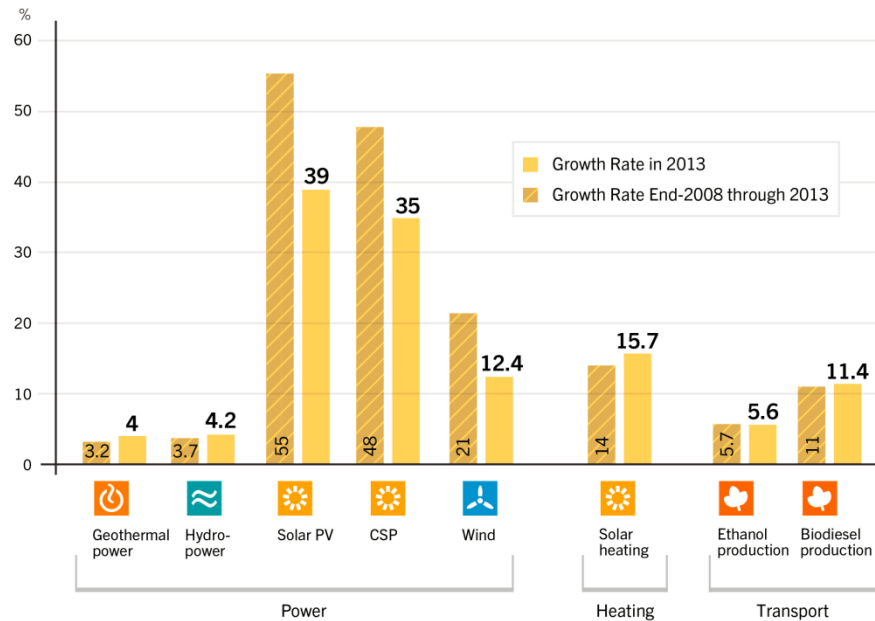
R&D into renewable energy makes reducing CO2 emissions cheaper and easier, but...

Non-dispatchable generation creates problems for the grid.

Modeling grid integration is difficult and expensive.

We would like to place bounds on the value of problem before we embark on a costly modeling exercise.

Average Annual Growth Rates of Renewable Energy Capacity and Biofuels Production, End-2008–2013



REN21. 2014. *Renewables 2014 Global Status Report* (Paris: REN21 Secretariat).



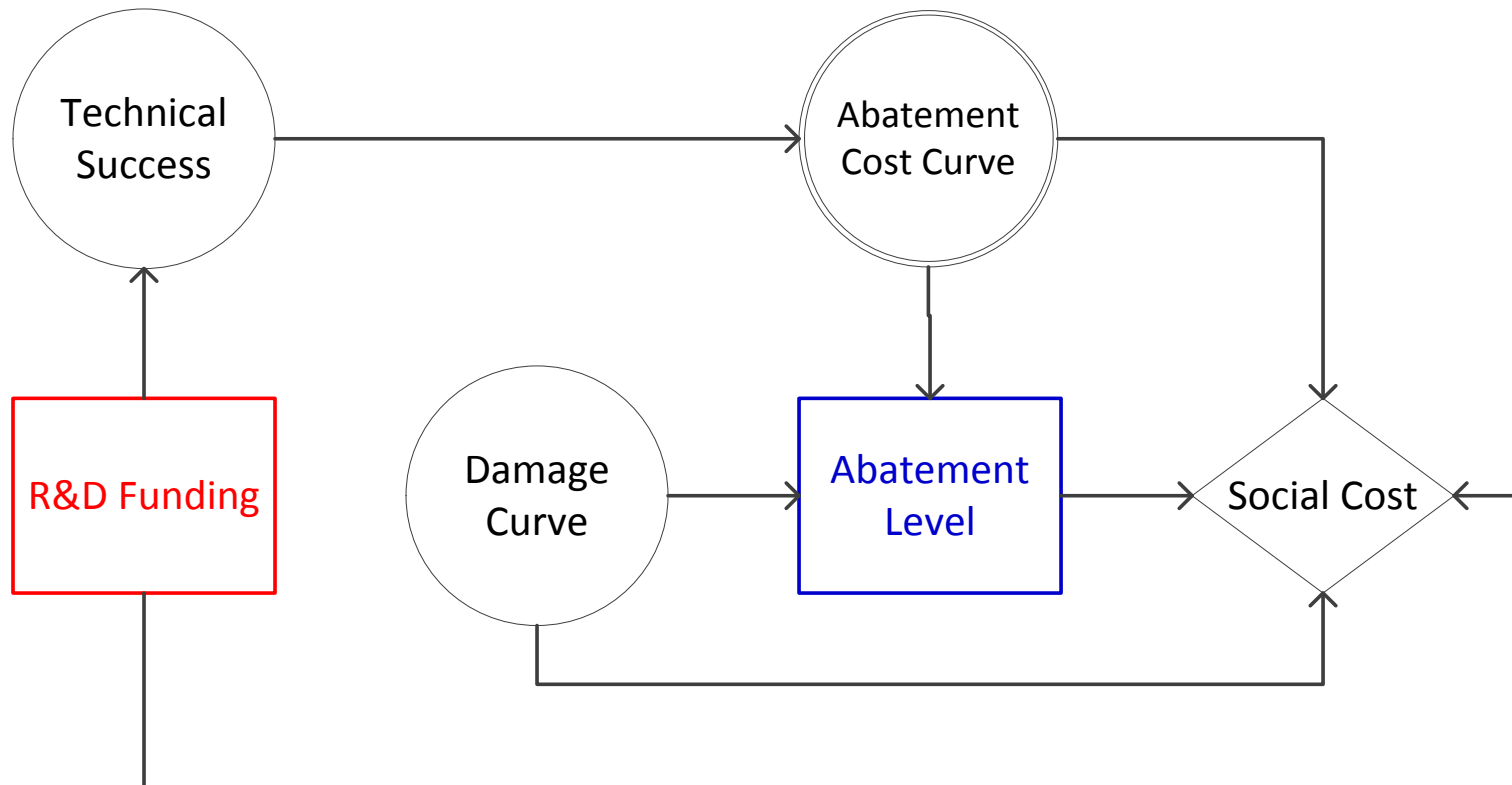
Strategy

- Construct a pair of two-stage stochastic models
 - The Budget Constrained Model (BCM).
 - The Overall Optimal Model (OOM).
- Use GCAM to estimate the effect of technological change and integration costs on the cost of abatement.
- Run the stochastic models under two extreme assumptions about grid integration costs.
 - Costly Integration
 - Free Integration

Influence Diagram

Two Stage Model

- Stage 1: Choose R&D portfolio.
- Stage 2: Choose abatement.

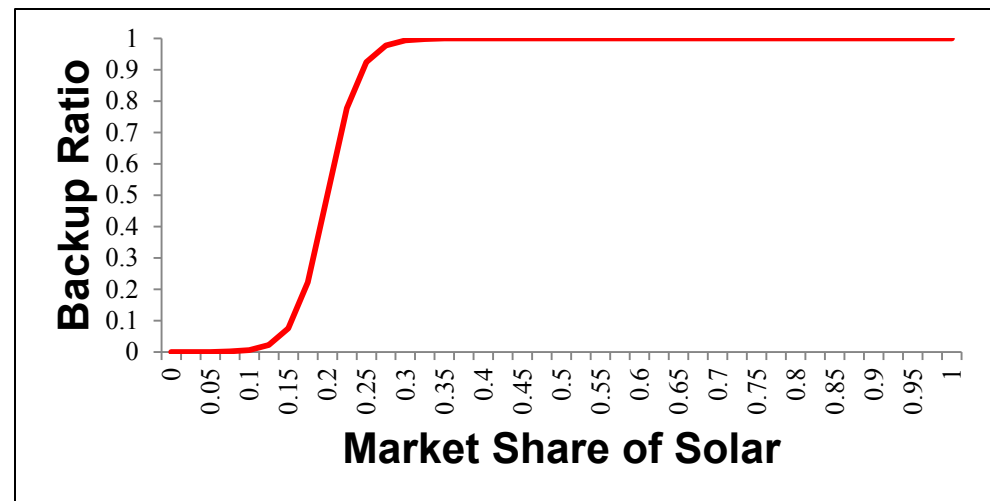


Grid Integration Assumptions

Costly Storage Assumption (CSA)

The GCAM default integration cost model.

- Two competing options for intermittency.
- Backup requires gas fired backup.



- Storage assumes PV is paired with storage at some additional cost

Free Storage Assumption (FSA)

Sets the cost of energy storage in GCAM to zero.

The R&D Menu and Portfolio

- Elicitations done by Baker, Chon and Kiesler (2008, 2008a, 2008b)
- DM chooses one funding level for each project.
- The resulting vector $x = [x_{ijk}] \forall ijk$ is the *Investment Portfolio*.

Technology (i)	Project (j)	Funding Level (MM 2008 \$) (k)			
		High (1)	Medium (2)	Low (3)	None (4)
1: Solar	1: Organic	386	154	39	0
	2: Inorganic	56	38	19	0
	3: 3rd Gen	519	224	52	0
2: Nuclear	1: Light Water Reactor	346	260	173	0
	2: High Temperature Reactor	3089	1544	772	0
	3: Fast Reactor	15443	4633	1158	0
3: CCS	1: Pre Combustion	N/A	830	116	0
	2: Chemical Loop	N/A	77	39	0
	3: Post Combustion	N/A	N/A	386	0

Effect of R&D on Abatement Cost

Given our investment portfolio x define a binary random indicator variable

$$Y_{ij}(x) = \begin{cases} 1 & \text{if project } ij \text{ is successful} \\ 0 & \text{otherwise} \end{cases}$$

and a_{ij} , a parameter that represents the effect of success in project i, j on the MAC.

Now, define a vector $s = (s_1, s_2, \dots, s_i)$; $s_i = \max_j [a_{ij}y_{ij}]$ to represent the state of technology.

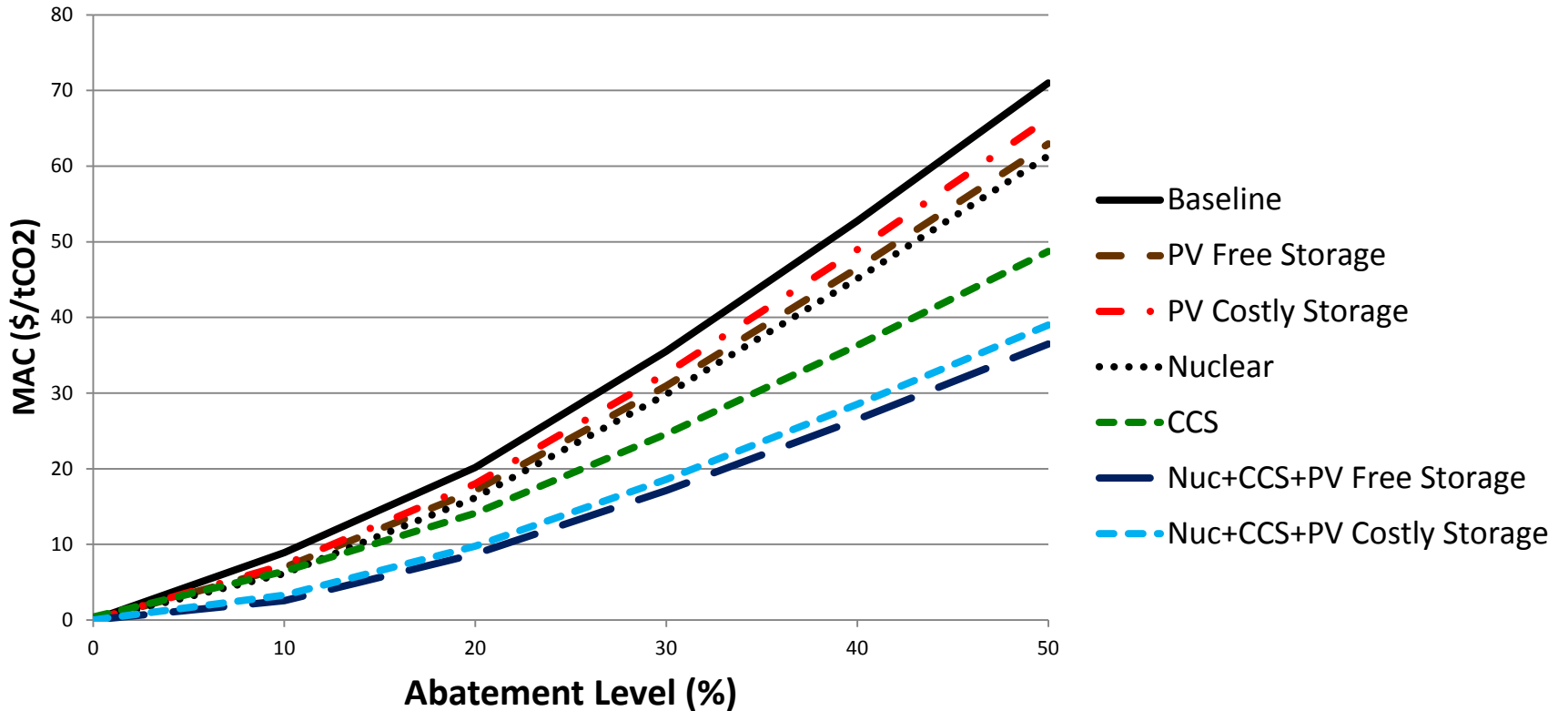
Let $\alpha(s)$ and $h(s)$ be random scalars that represent the combined effect of all of the technological successes corresponding to technological state s , on the Marginal Abatement Cost (MAC).

Now, define the MAC:

$$\widetilde{MAC}(\mu; \alpha(s), h(s)) = (1 - \alpha(s))(MAC(\mu) - h(s)MAC(0.5))$$

Estimating Technology's Effect on the MAC Curve

$$\widetilde{MAC}(\mu: \alpha(s), h(s)) = (1 - \alpha(s))(MAC(\mu) - h(s)MAC(0.5))$$



(After Baker and Solak, 2011)

The Budget Constrained Model (BCM)

$$\min_{x_{ijk}} \left(E_{s,z} \left[\min_{\mu} [C(\mu; \alpha(s), h(s)) + ZD(\mu)] \right] \right)$$

s.t.

$$\sum_{ijk} x_{ijk} F_{ijk} \leq B$$

$$\sum_k x_{ijk} = 1 \quad \forall i, j$$

$$x_{ijk} \in \{0,1\}$$

Where

B	Budget Constraint
Z	Stochastic damage risk multiplier
α, h	Technological change parameters
x_{ijk}	Binary decision variable to fund project ijk
F_{ijk}	Cost of funding project ijk
s	Vector representing the state of technology

The Overall Optimal Model

$$\text{Min}_{x_{ijk}} \left(\beta \sum_{ijk} x_{ijk} F_{ijk} + E_{s,z} \left[\min_{\mu} [C(\mu: \alpha(\mathbf{s}), h(\mathbf{s})) + ZD(\mu)] \right] \right)$$

st

$$\sum_k x_{ijk} = 1 \quad \forall i, j$$

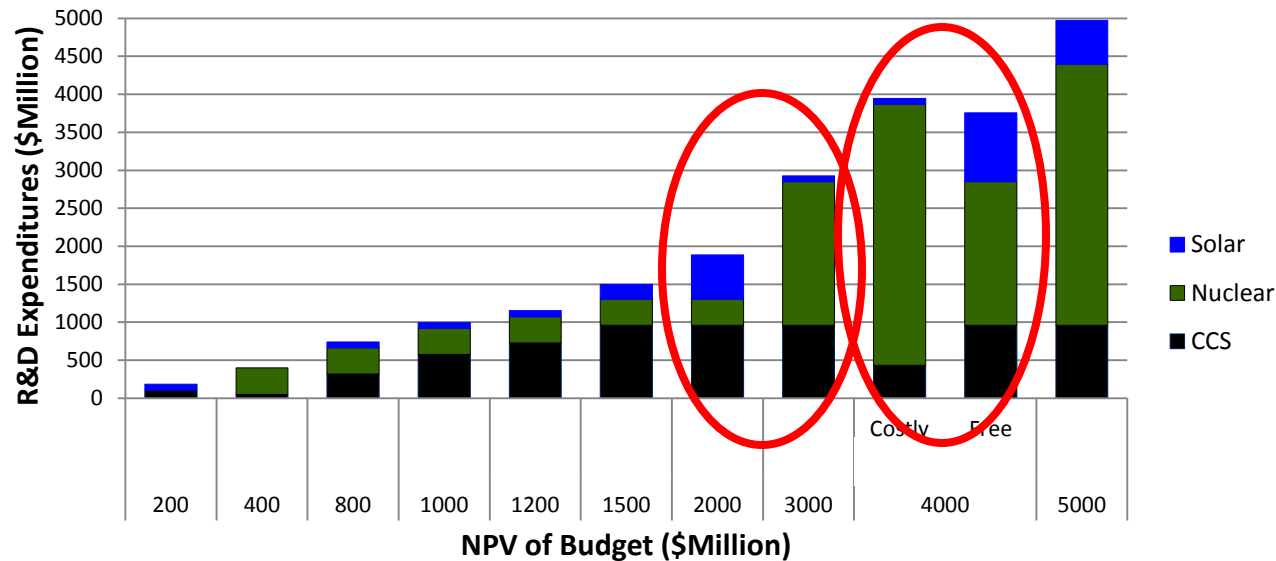
$$x_{ijk} \in \{0,1\}$$

Where

β is an opportunity cost multiplier that reflects the opportunity cost of R&D investments.

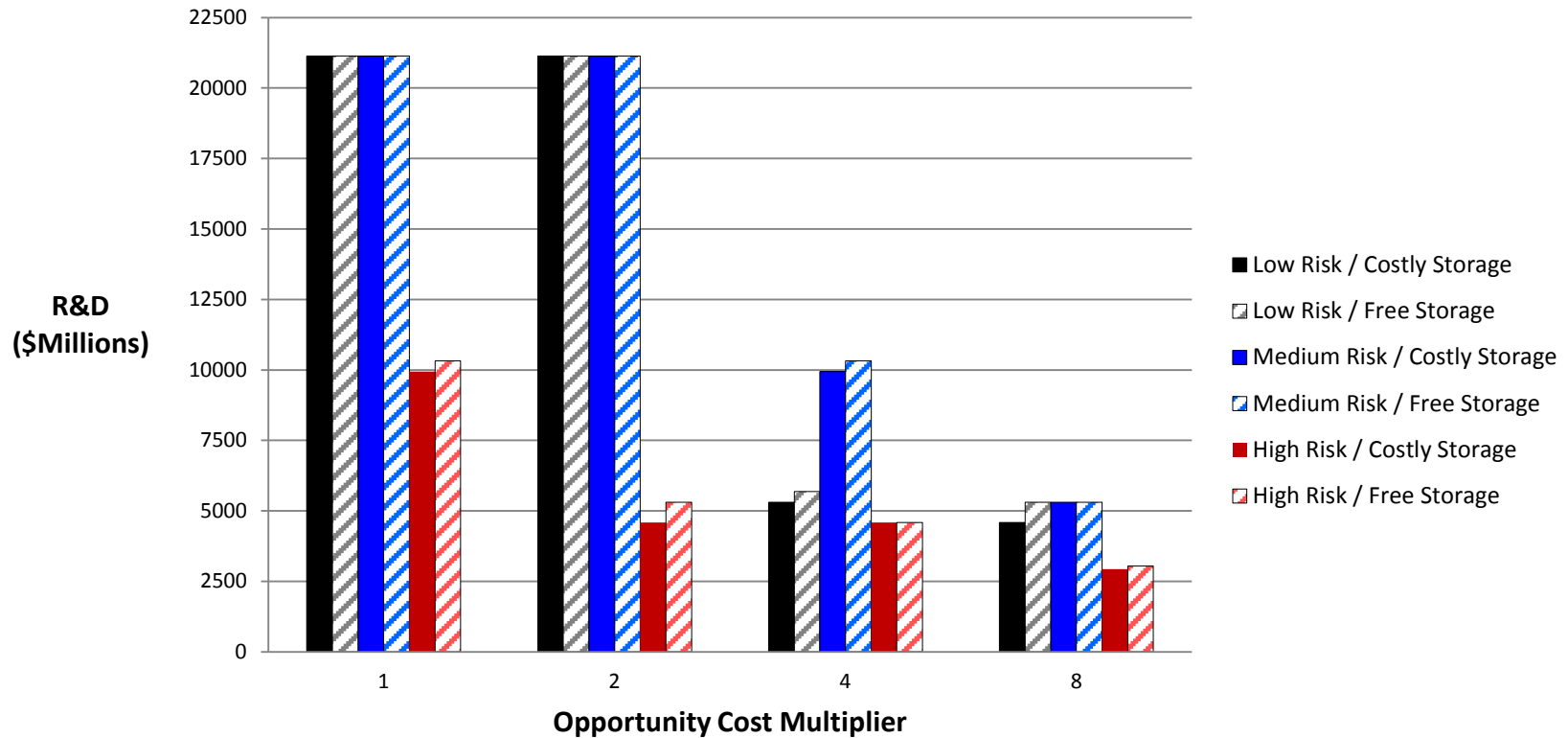
The OOM moves the budget constraint to the objective function and adds an opportunity cost multiplier.

Budget Constrained Model



- Grid integration assumptions have little impact – only one difference.
- Lumpy problem – moving from 2000-3000 greatly increases nuclear at the expense of solar.

Overall Optimal Model



- Grid integration assumptions make a difference here.

Overall Optimal Model

Climate Damage Risk Level	Cost Multiplier	Integration Cost	CCS			Nuclear			Solar			Total R&D cost (\$ MM)
			Pre Combustion	Chemical Looping	Post Combustion	Light Water Reactors	High Temp. Reactors	Fast reactors	Organic	Inorganic	3 rd Gen.	
Low	1	Costly	386	56	519	346	3089	15443	830	77	386	21132
		Free	386	56	519	346	3089	15443	830	77	386	21132
	2	Costly	386	56	519	346	3089	15443	830	77	386	21132
		Free	386	56	519	346	3089	15443	830	77	386	21132
	4	Costly	386	56	519	346	3089	0	830	77	0	5303
		Free	386	56	519	346	3089	0	830	77	386	5689
	8	Costly	386	56	519	346	3089	0	116	77	0	4589
		Free	386	56	519	346	3089	0	830	77	0	5303
Medium	1	Costly	386	56	519	346	3089	15443	830	77	386	21132
		Free	386	56	519	346	3089	15443	830	77	386	21132
	2	Costly	386	56	519	346	3089	15443	830	77	386	21132
		Free	386	56	519	346	3089	15443	830	77	386	21132
	4	Costly	386	56	519	346	3089	4633	830	77	0	9936
		Free	386	56	519	346	3089	4633	830	77	386	10322
	8	Costly	386	56	519	346	3089	0	830	77	0	5303
		Free	386	56	519	346	3089	0	830	77	0	5303
High	1	Costly	386	56	519	346	3089	4633	830	77	0	9936
		Free	386	56	519	346	3089	4633	830	77	386	10322
	2	Costly	386	56	519	346	3089	0	116	77	0	4589
		Free	386	56	519	346	3089	0	830	77	0	5303
	4	Costly	386	56	519	346	3089	0	116	77	0	4589
		Free	386	56	519	346	3089	0	116	77	0	4589
	8	Costly	386	56	519	346	1544	0	0	77	0	2928
		Free	386	56	519	346	1544	0	116	77	0	3044

- Investments in Organic and 3rd gen solar increase under the FSA

Conclusions

- Under a budget constraint grid integration assumptions have little impact on the optimal R&D portfolio.
- In the absence of a budget constraint grid integration assumptions do make a difference.
- Getting grid integration costs right depends on the question being asked: how to allocate a exogenously specified budget, or what size the budget should be.

Questions?

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Definitions

- DICE:** The Dynamic Integrated Model of the Climate and Economy (Nordhaus 2008).
- GCAM:** The Global Change Assessment Model (JGCRI 2012).
- Integration Cost:** Any cost imposed by intermittency.
- Abatement:** A reduction in emissions below the business-as-usual baseline.

Abatement and Damage Functions

- Damages

$$D(\mu) = M_0(Q - M_1\mu)$$

Where M_0, M_1 : Parameters of the damage function.

Q : BAU quantity of carbon emissions.

μ : Abatement as a proportion of BAU emissions

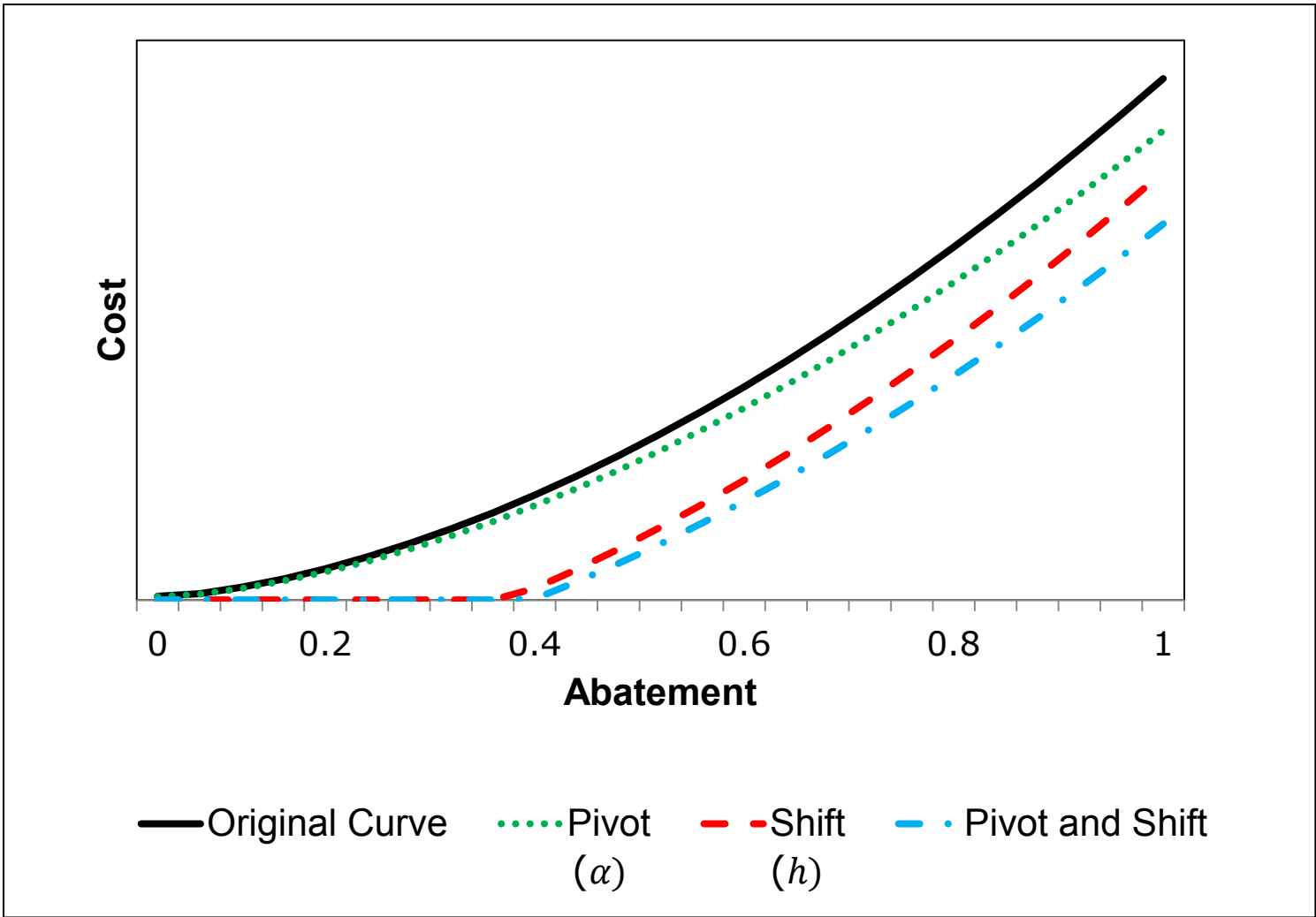
- Abatement Cost

$$C(\mu) = b_0\mu^{b_1}$$

Where b_0, b_1 are calibration parameters.

This work considers abatement cost in terms of the Marginal Abatement Cost (MAC).

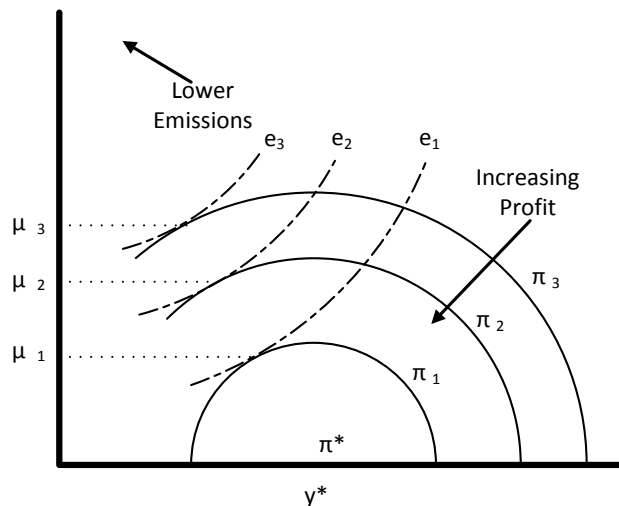
Technological Change and the Abatement Cost Function



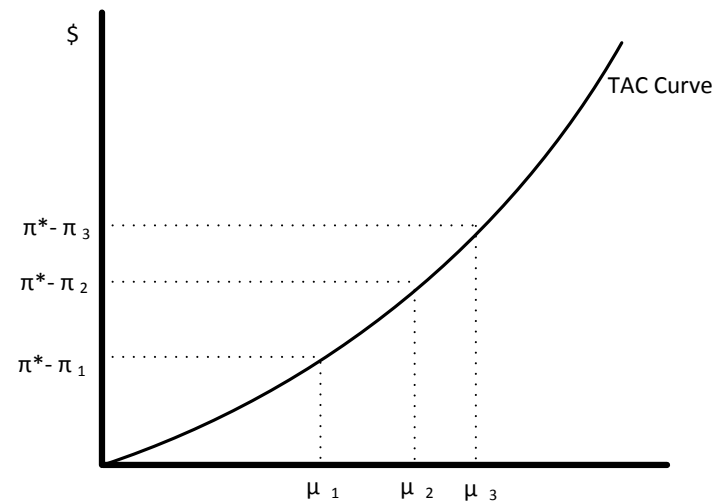
The Abatement Cost Function

Abatement: Reduction in emissions below some baseline.

Abatement cost: Difference in profit/GDP with and without an emissions constraint, WRT abatement level.



(a) Output



(b) Abatement

(a) The abatement problem, (b) The TAC curve (Adapted from (McKittrick 1999, 306-314)).

Marginal Abatement Cost (MAC): $MAC(\mu) = TAC'(\mu)$

Calibration

- After Peng (2010)

$$D(\mu) = M_0(S - M_1\mu)^2$$

Where S is the initial emissions stock (2.5×10^{12} tc) and under the BAU ($\mu = 0$) scenario the NPV of damages is \$17.7 trillion.

$$D(\mu = 0) = M_0S^2 = \$17.7 \times 10^{12} \rightarrow M_0 = 2.74$$

Now let $\mu_0 = 0.462$ be average abatement from 2005-2095 in the optimal case, and the NPV of damages be \$13.54 trillion.

$$D(\mu_0) = 2.74(S - M_1\mu_0)^2 = \$13.54 \times 10^{12} \rightarrow M_1 = 0.6$$

Calibration

- Abatement cost in DICE is given by

$$c(\mu) = b_0\mu^{b_1}$$

Recognize that in the optimal case $\frac{\partial c(\mu)}{\partial \mu} = \frac{\partial D(\mu)}{\partial \mu} = 0$

From DICE $b^1 = 2.8$

Solving yields $b_0 = 10.43$ and

$$C(\mu) = 10.43\mu^{2.8}$$