
Uncertainty and Endogenous Technical Change: Applying Expert Elicitations to Inform Climate Policy

Erin Baker

University of Massachusetts, Amherst

September 28, 2007

Prepared for **Conference on the Economics of
Climate Change and Sustainable Development**

What to do about climate change?

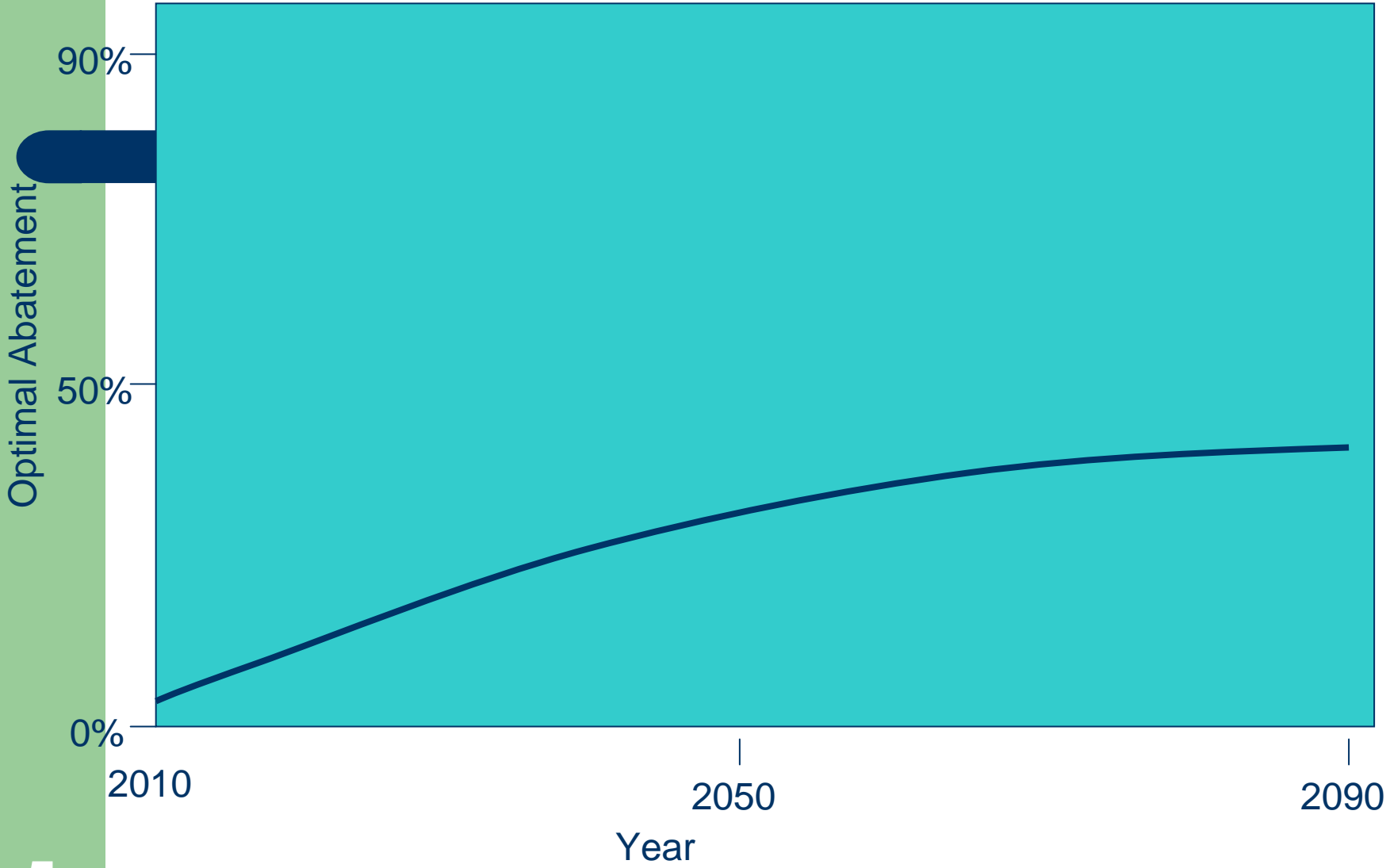
- What is the optimal path for a carbon tax and/or an emissions path?
 - Emissions taxes
 - Cap and trade
 - Emissions standards
- What is the optimal investment path in a portfolio of technology R&D projects?
 - Government funded R&D
 - R&D subsidies
 - Technology standards

Today's Talk

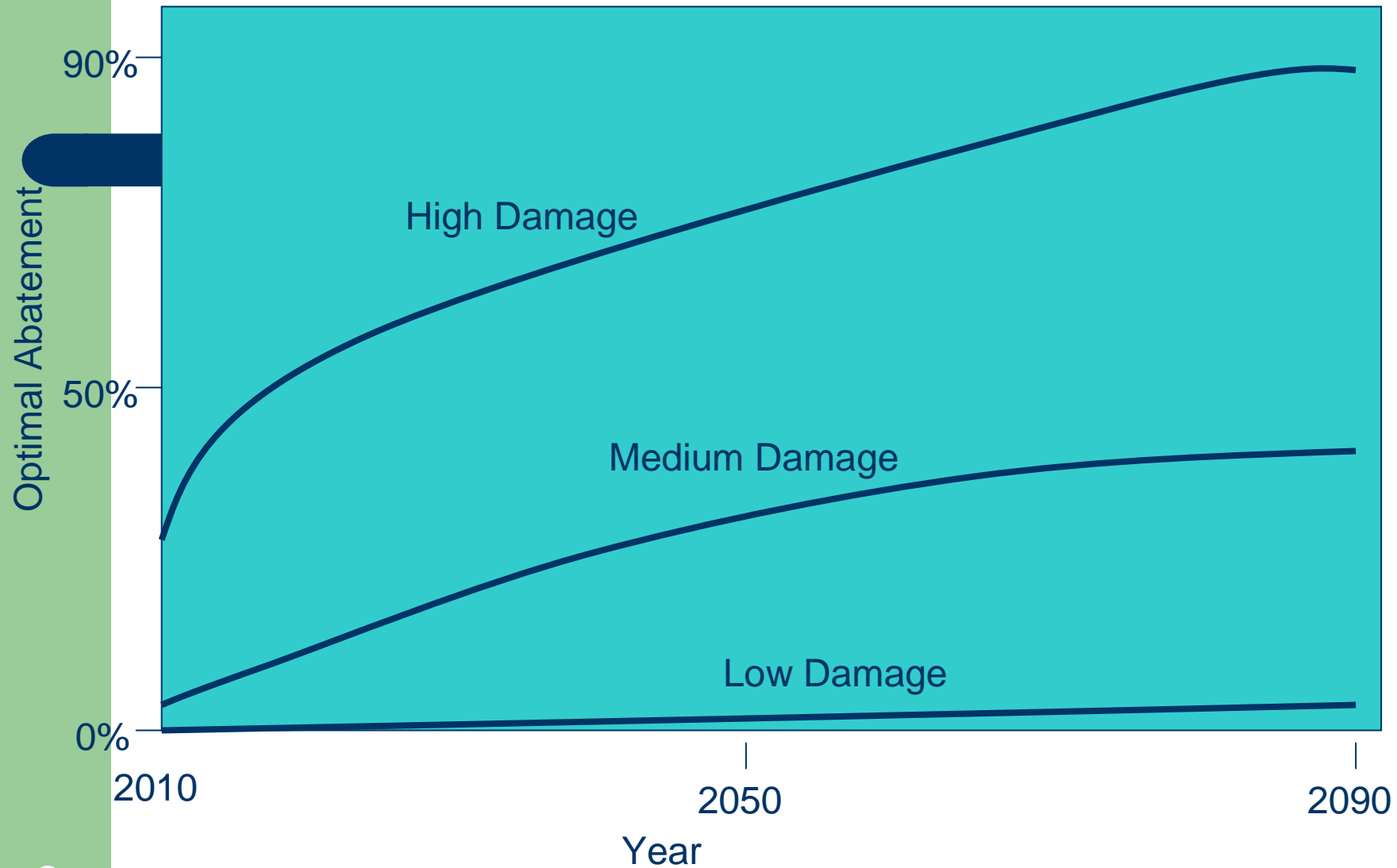
- Background: Decision Making Under Uncertainty
 - Optimal Abatement Under Uncertainty
 - Uncertainty and Endogenous Technical Change
 - Uncertainty in damages and uncertainty in technical change interact, so must model both.
- A Framework, applied to Solar PV R&D
 - Expert Elicitations
 - Impacts on Abatement Cost Curve
 - Random Returns to R&D
- Future Work
 - Implement probabilistic data into policy models

Decision Making Under Uncertainty

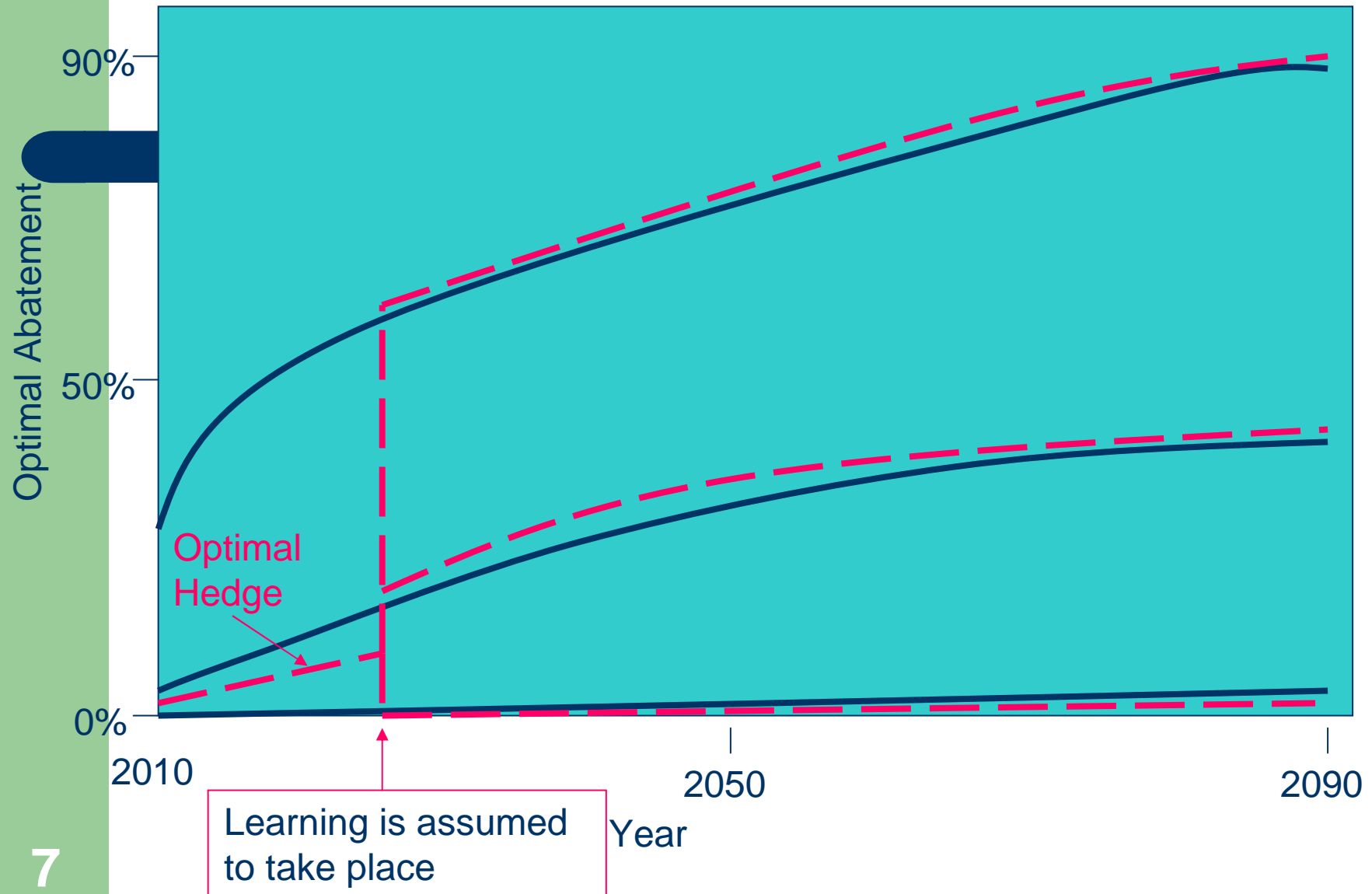
A stylized optimal abatement path under specific, deterministic assumptions



Three stylized optimal abatement paths under different specific, deterministic assumptions



A stylized optimal near term abatement path under specific, probabilistic assumptions



Impacts of Uncertainty and Learning on optimal abatement

- Baker (2005), Gollier et al. (2000), Karp and Zhang (2006), Keller et al. (2004), Kolstad (1996), Manne (1996), Nordhaus and Popp (1997), Pizer (1999), Ulph and Ulph (1997), Webster (2002)
- In the absence of learning, optimal abatement is probably higher as uncertainty increases.
- Assuming learning, optimal abatement is probably lower as uncertainty increases.
 - Prudence can reverse this.
 - Certain increases in risk reverse this.
- Numerical impact of uncertainty (with learning) appears small.
- Value of Information of better, sooner information is high.

Endogenous Technical Change

- Buonanno et al. (2003), Goulder and Mathai (2000), Goulder and Schneider (1999), Manne and Richels (2004), Nordhaus (2002), Popp (2004, 2006), Schneider and Goulder (1997), Sue Wing (2003), van der Zwaan et al. (2002), Newell (1997), Newell et al. (1999).
- Most of the work has been deterministic
 - deterministic damages and/or stabilization goal
 - deterministic technical change

Uncertainty Matters

Explicitly including uncertainty and endogenous technical change

Baker, E., Clarke, L., and Weyant, J., *Optimal Technology R&D in the Face of Climate Uncertainty*. ***Climatic Change*** 75:157 – 180 (2006)

Baker E. and Adu-Bonnah, K., *Investment in Risky R&D Programs in the face of Climate Uncertainty*. ***Energy Economics***, (Forthcoming).

Baker E. and E. Shittu, *Profit Maximizing R&D Investment in Response to a Random Carbon Tax*, ***Resource and Energy Economics***, 28:105- 192 (2006)

Socially Optimal R&D investment

Baker & Adu-Bonnah (2006)

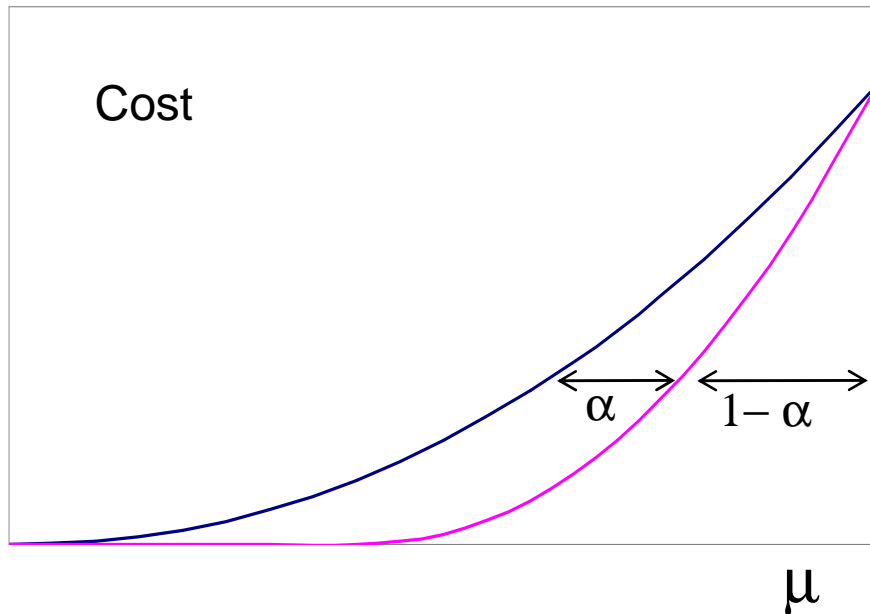
- We consider how optimal R&D investment is impacted by
 - The choice of R&D program (greener vs. cleaner);
 - The riskiness of R&D program; and
 - Uncertainty and learning about climate damages.

Integrated Assessment Model

- William Nordhaus's DICE
 - Optimal Growth + Climate Model
 - Social Planner chooses how to divide income between consumption, investment, and emissions reduction.
 - Added uncertainty, using stochastic programming.
 - First 5 periods decisions are made under uncertainty
 - After 5 periods the world splits into three damage scenarios.
-

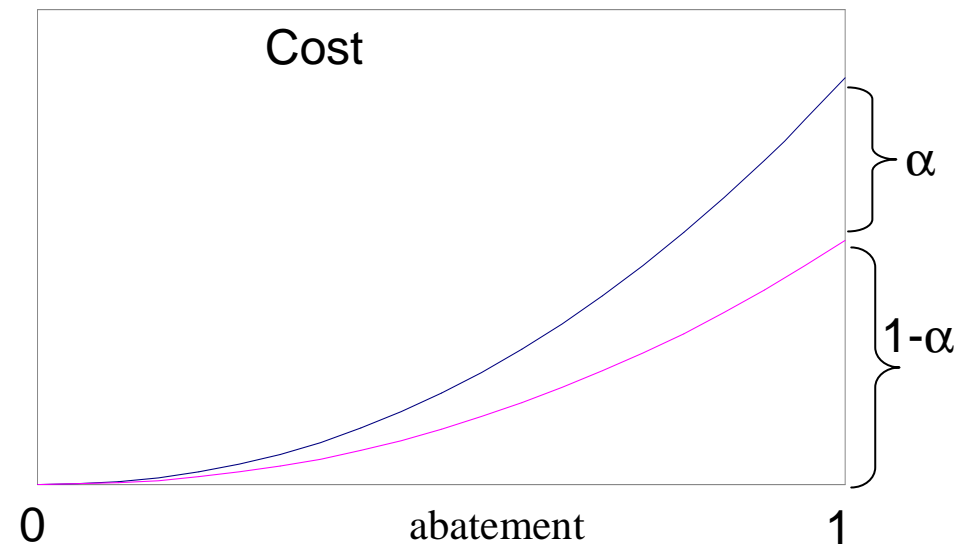
We model technical change in two ways

“Cleaner Technologies”



The abatement cost curve pivots to the right

Greener Technologies



The abatement cost curve pivots downward

Integrated Assessment Model

- Added R&D as a decision variable.
 - One time decision in 1st period before learning
 - Cost reduction implemented in 50 years, after learning about damages.

Certain R&D Program

$$\alpha = \bar{\alpha}$$

Risky R&D Program

$$\alpha = \begin{cases} \text{value} & \text{probability} \\ 0 & 1 - \bar{\alpha} \\ 1 & \bar{\alpha} \end{cases}$$

We represent increasing risk in climate damages in two different ways.

Increasing Probability

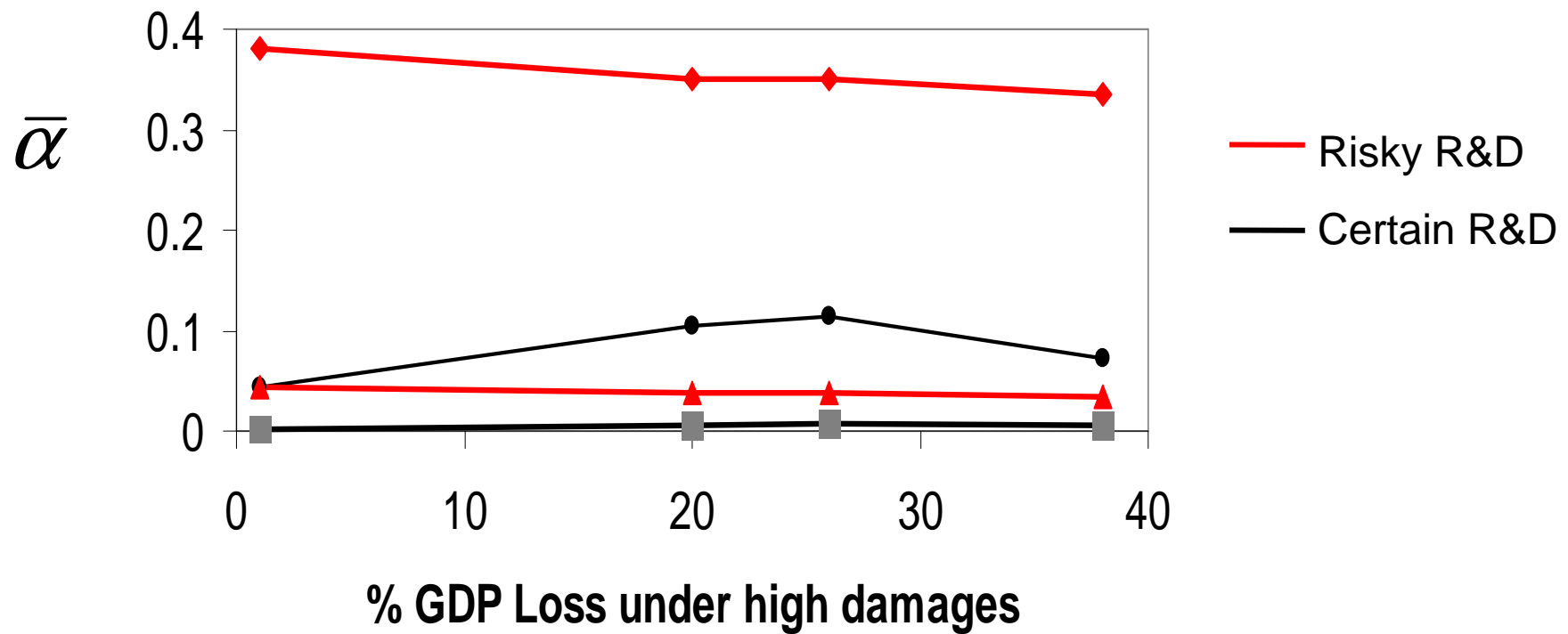
Probability of $\theta = 0$	0%	19.8%	55%	91.7%
Probability of $\theta = .0035$	100%	78.4%	45%	0%
Probability of $\theta = .042$	0%	1.8%	5%	8.3%

Increasing Damages

Value of high damage θ^H	--	.042	.057	.1
Probability of $\theta = 0$	0%	19.8%	20.3%	20.8%
Probability of $\theta = .0035$	100%	78.4%	78.4%	78.4%
Probability of $\theta = \theta^H$	0%	1.8%	1.3%	0.8%

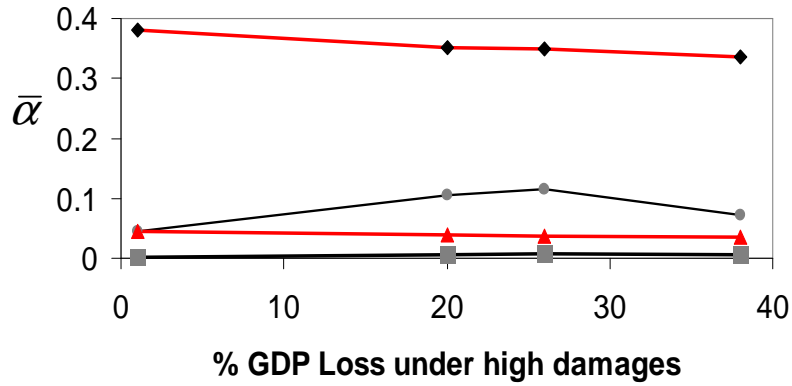
Optimal R&D investment under uncertainty about damages

Greener Technologies Increasing Damages

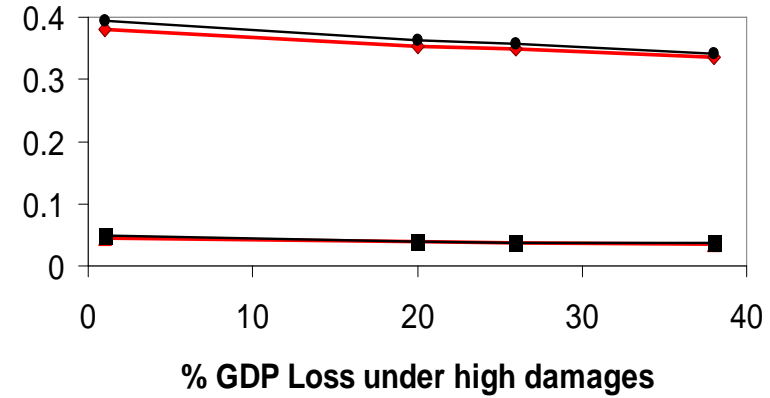


MPS in damages

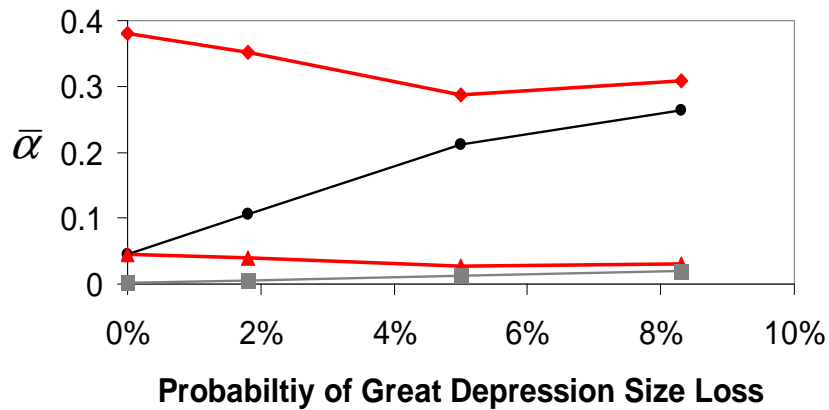
Greener Technologies
Increasing Damages



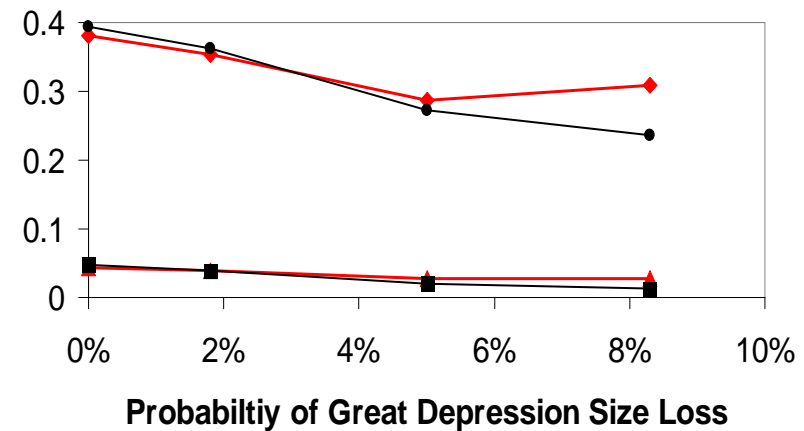
Cleaner Technologies
Increasing Damages



Increasing Probability



Increasing Probability



— Risky R&D
— Certain R&D

MPS in damages →

Conclusions for socially optimal R&D

Baker & Adu-Bonnah (2006)

- Optimal investment is significantly **higher** in R&D programs aimed at reducing the cost of low-carbon technologies when the program is **riskier**.
 - Policies should be aimed at increasing the probability of a breakthrough.
 - **Investment in alternative technologies should be higher than deterministic studies would indicate.**
 - **Rationale for government policy, since private sector tends to be risk-averse.**
 - Result is robust to many different probability distributions over climate damages.

Conclusions for socially optimal R&D

Baker & Adu-Bonnah (2006)

- The risk-profile of R&D programs aimed at reducing emissions in conventional technologies is largely **unimportant**.
 - Policies should be aimed at maximizing expected value of technical change.
 - Deterministic studies should give a good approximation of appropriate level of investment.
 - **Less rationale for government policy.**
 - If the probability of full abatement is high, then investment in risky program increases.

Conclusions for socially optimal R&D

Baker & Adu-Bonnah (2006)

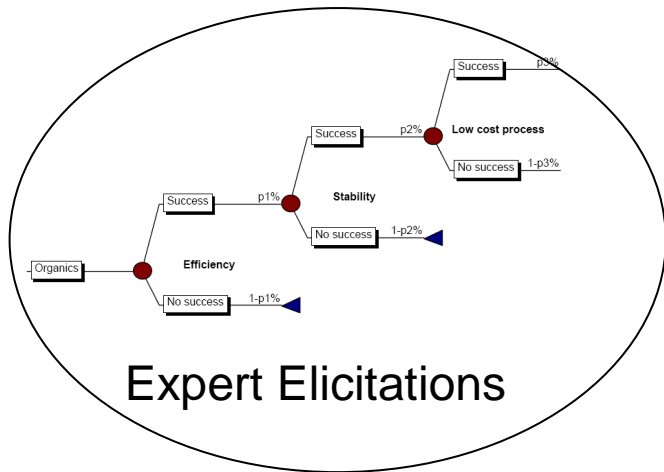
- The level of investment in a climate-technology R&D program depends on
 - How the technology impacts the abatement cost curve;
 - The riskiness of the R&D program; and
 - The probability distribution over climate damages.

Conclusions for socially optimal R&D

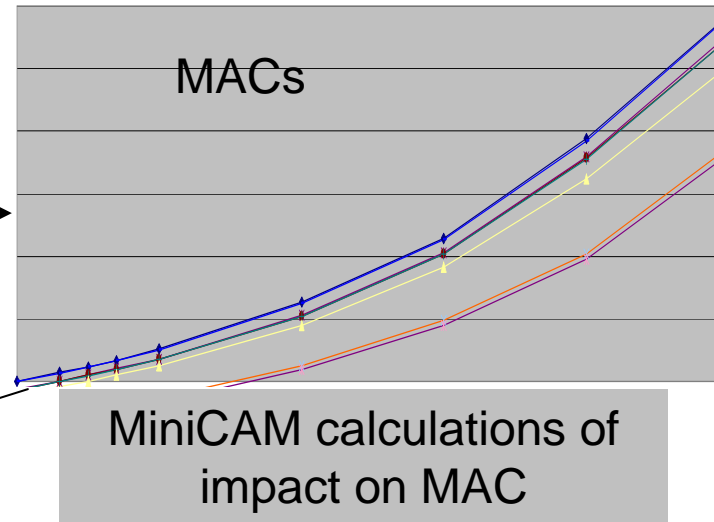
Baker & Adu-Bonnah (2006)

- The level of investment in a climate-technology R&D program depends on
 - How the technology impacts the abatement cost curve;
 - The riskiness of the R&D program; and
 - The probability distribution over climate damages.
- Therefore, we need to answer some questions:
 - *How will different technologies impact the MAC, if successful?*
 - *What is the probability distribution over different outcomes of technical change?*

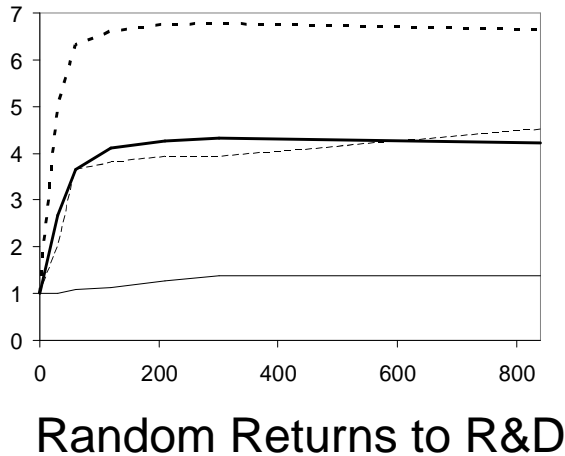
Research Plan



definitions
of success

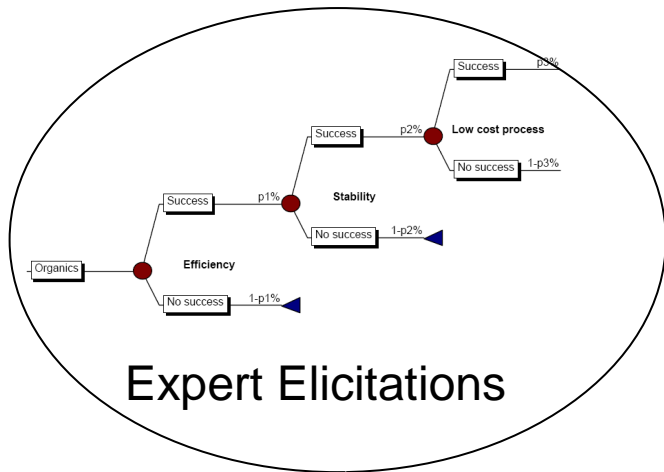


probabilities

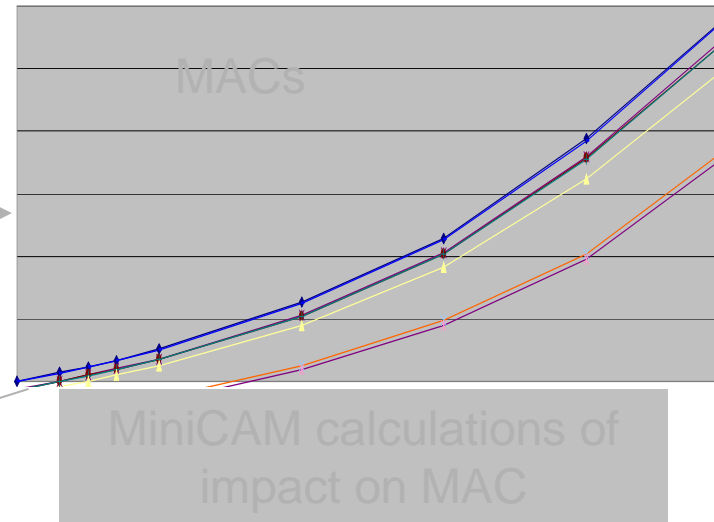


- Collect Expert Assessments of Potential R&D Projects
- Determine Impact on MAC, using MiniCAM
- Develop portable representations of the probabilistic impact of technical change.

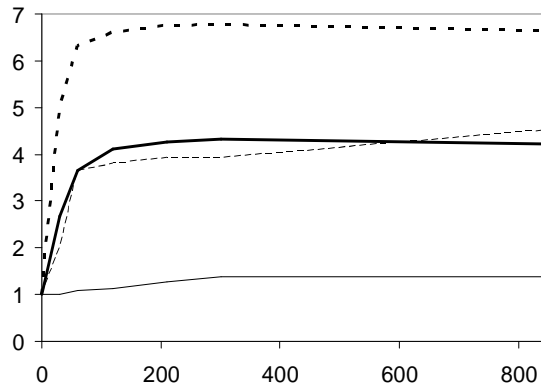
Research Plan



definitions of success



probabilities



Random Returns to R&D

- **Collect Expert Assessments of Potential R&D Projects**
- Determine Impact on MAC, using MiniCAM
- Develop portable representations of the probabilistic impact of technical change.

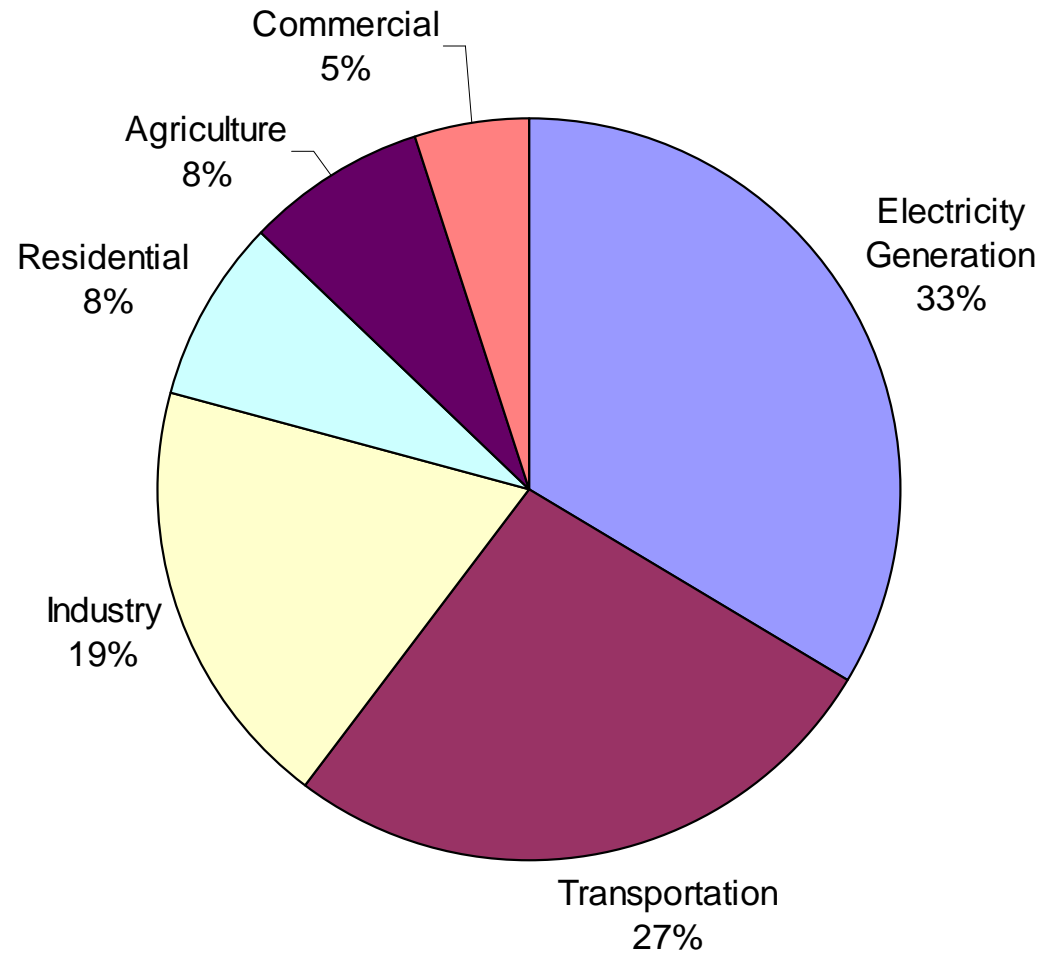
Expert Elicitation

- Elicit probabilities from experts.
- What is the probability of technical success given a particular funding trajectory?

Expert Elicitation

- Elicit probabilities from experts.
- What is the probability of technical success given a particular funding trajectory?
- Scientific advance is lumpy – it can't be inferred from past data.
 - *To the extent that probability of achieving success depends on breakthroughs, what has happened with other technologies will not offer much to differentiate paths that are particularly promising.*

US Greenhouse Gas Emissions Allocated to Economic Sector : April 2002



Assessments:

Identify More Specific Technical Directions within Broad Categories

Advanced Solar PVs
Carbon Capture and Storage & Combustion
Nuclear Fission
Bio-electricity
Wind and Solar Grid Integration
Biofuels
Batteries

<i>Advanced Solar:</i>
Purely Organic
CIGS
New Inorganic
3 rd Generation

Each definition of success results in a cost per kWh

Technology	Definition of success	Cost (cent/kWh)	Cost improvement metric
1a. Purely Organic	15%, 30 year, \$50/m ²	5.0	7.2
1b. Purely Organic	31%, 15 year, \$50/m ²	3.0	12
2. New Inorganic	15%, 30 year, \$50/m ²	5.0	7.2
3. CIGS	15%, 30 year, \$50/m ²	5.0	7.2
4. 3rd Gen	36%, 30 year, \$100/m ²	2.9	12.4

Assessment Survey

Assumptions: U.S. government funding trajectory of \$15M/year for 10 years, i.e., 10 full sized research groups with approximately 10 graduate students each, with technology to leave university labs after that.

By the end of that time, what is the probability that:
At least one molecule will be found that achieves 15% efficiency
Probability: _____.

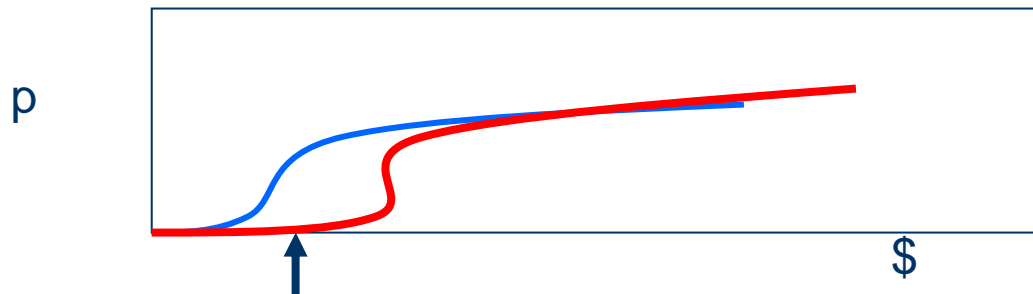
Rationale:

Assessment: Purely Organic Solar Cells

Need Estimates for	Funding Trajectory \$15M/yr 10 yrs	ex1	ex2	ex3
P1	Efficiency 15%	.85	.9	.8
P2	Stability 30 years	.50	.3	.5
P3	Low cost deposition (total < \$50/m ²)	.90	.5	.25
P4	Low cost substrate (total < \$50/m ²)	.90	.3	.1
Total		.34	.04	.01

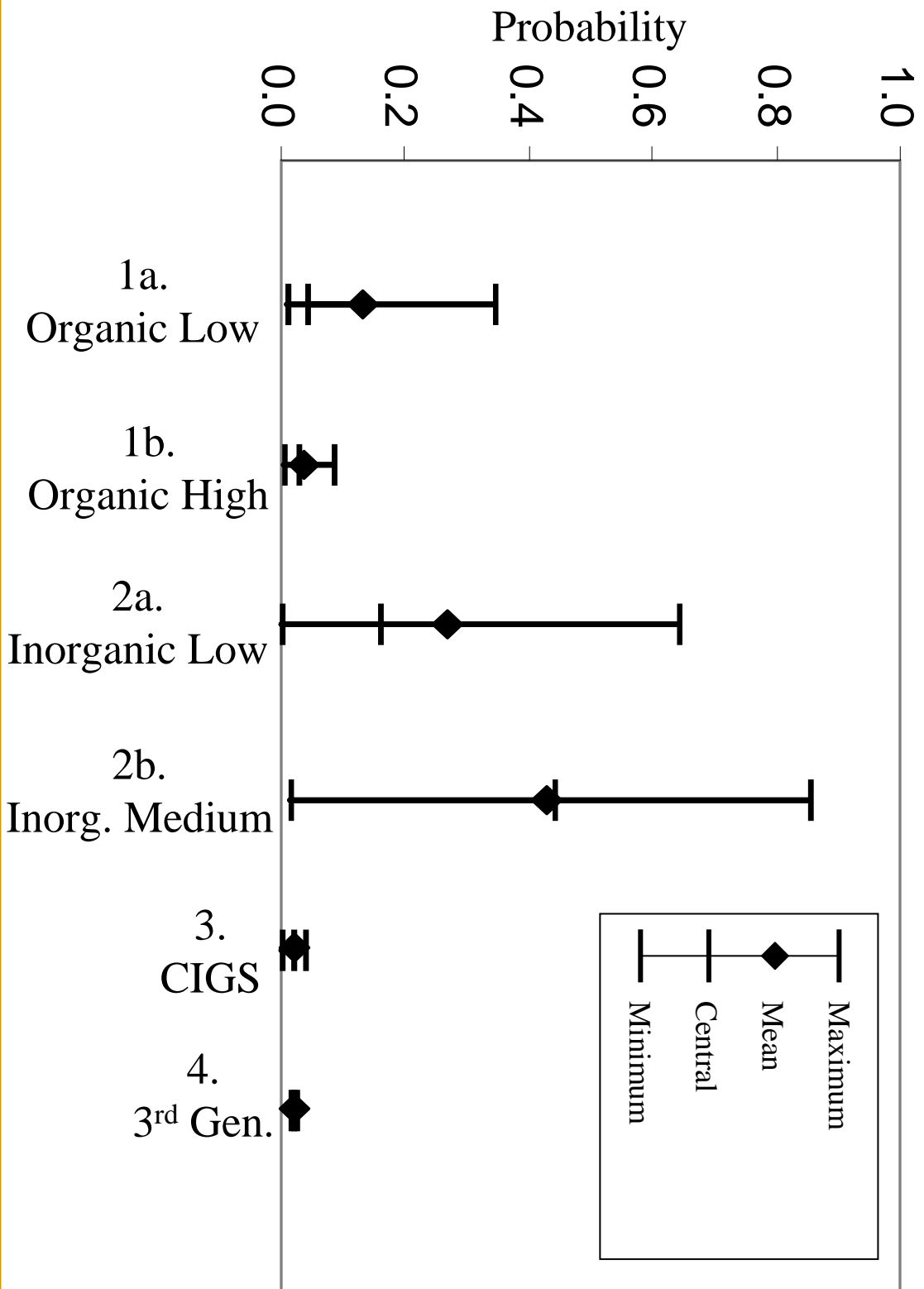
Assessment: Purely Organic Solar Cells

Need Estimates for	Funding Trajectory \$15M/yr 10 yrs	ex1	ex 2	ex 3
P1	Efficiency 15%	.85	.9	.8
P2	Stability 30 years	.50	.3	.5
P3	Low cost deposition (total < \$50/m ²)	.90	.5	.25
P4	Low cost substrate (total < \$50/m ²)	.90	.3	.1
Total		.34	.04	.01

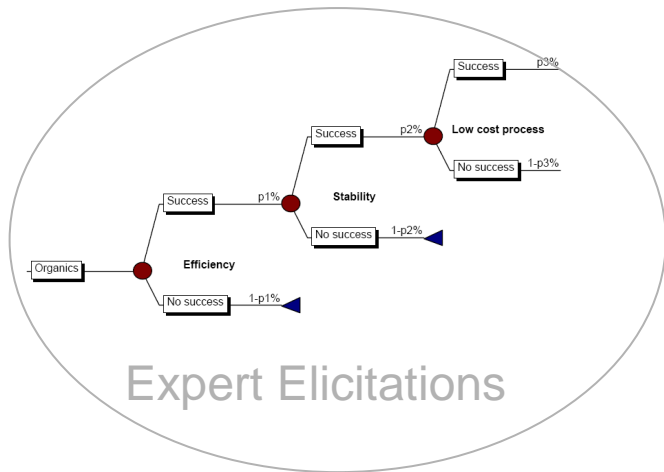


Assessment: Four Categories

Technology	Funding Trajectory	Definition of success (Efficiency, stability, cost)	Ex 1	Ex 2	Ex 3
Purely organic	\$10M 10yrs	15%; 30 yrs; \$50/m ²	.34	.04	.01
	\$80M 15yrs	31%; 15 yrs; \$50/m ²	.03	.08	.006
CIGS	\$15M 10yrs	15%; 30 yrs; \$50/m ² ; no indium shortage	.04	0	.02
New inorganic	\$5M 10yrs	15%; 30 yrs; \$50/m ²	.64	.16	.001
	\$10M 10yrs	15%; 30 yrs; \$50/m ²	.85	.43	.01
	\$20M 10yrs	15%; 30 yrs; \$50/m ²	.85	.43	.02
3 rd Generation	\$15M 10yrs	36%; 30 yrs; \$100/m ²	.02	.02	.01

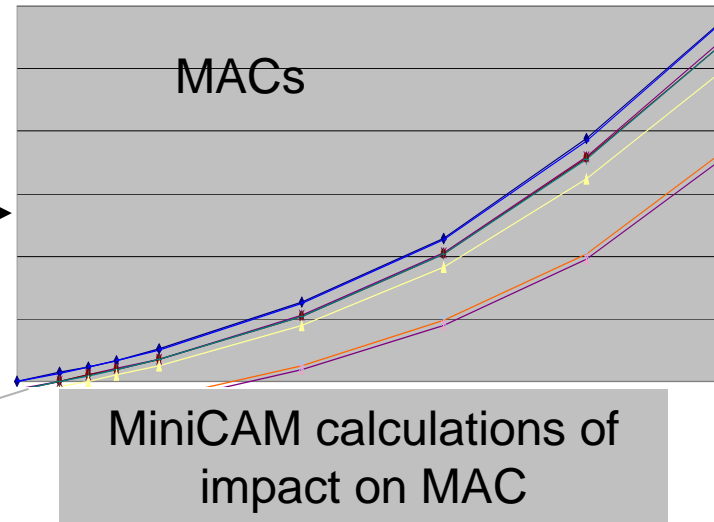


Research Plan

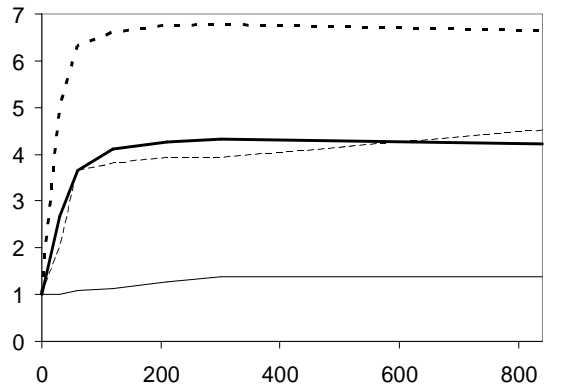


Expert Elicitations

definitions
of success



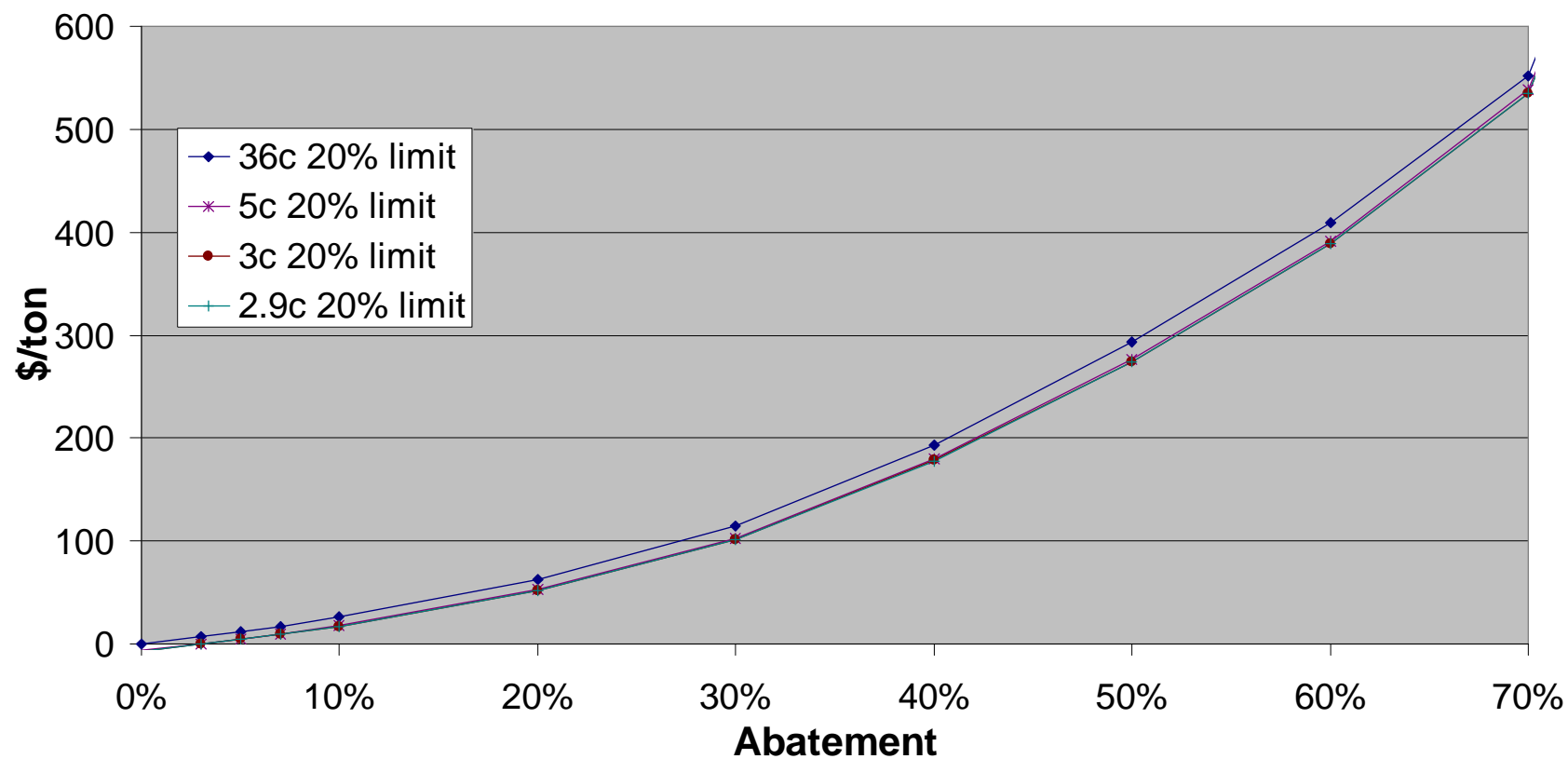
probabilities



- Collect Expert Assessments of Potential R&D Projects
- Determine Impact on MAC, using MiniCAM
- Develop portable representations of the probabilistic impact of technical change.

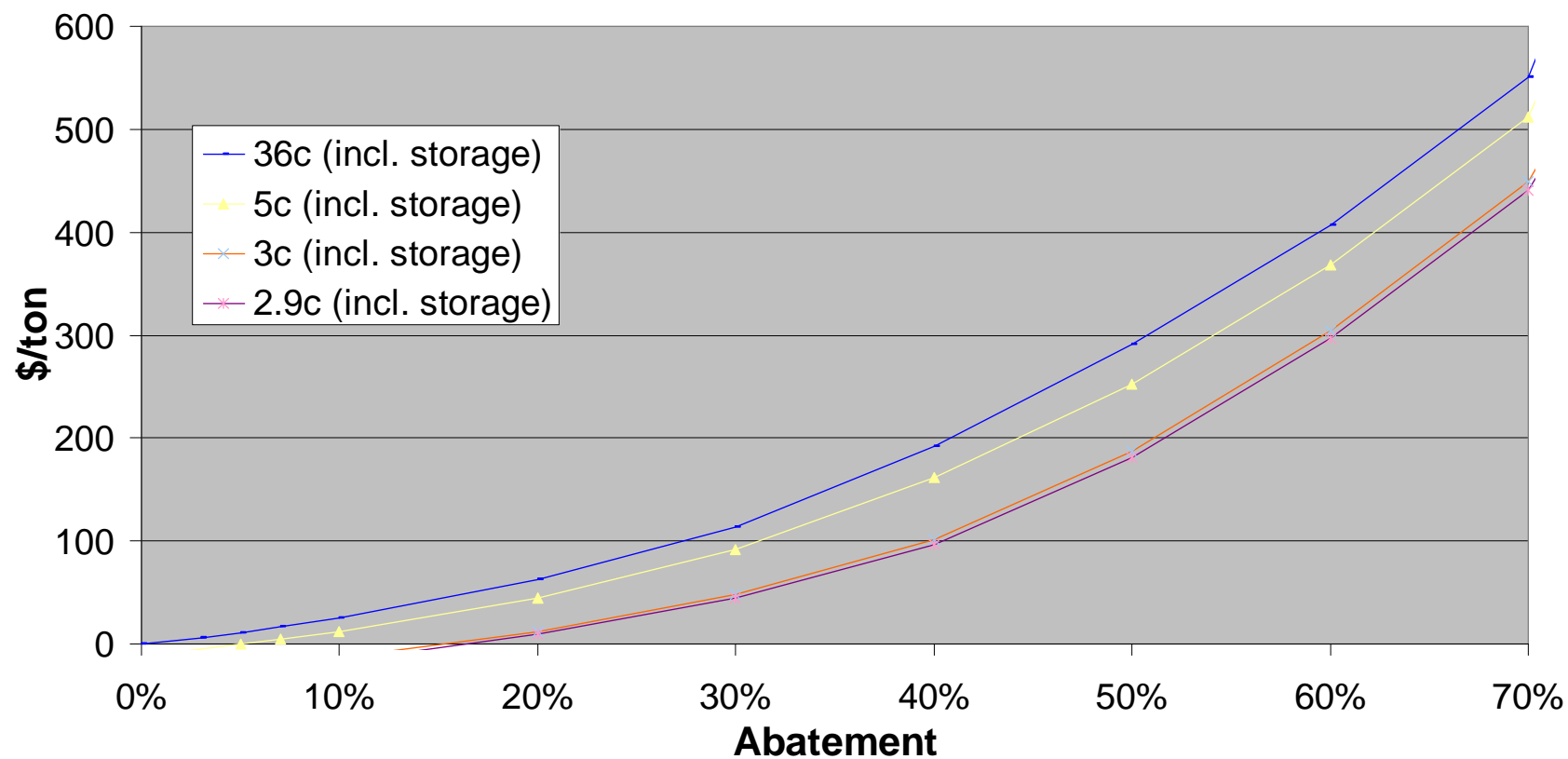
Impact of solar on the MAC: 20% capacity limit

Marginal Cost of Abatement 2050



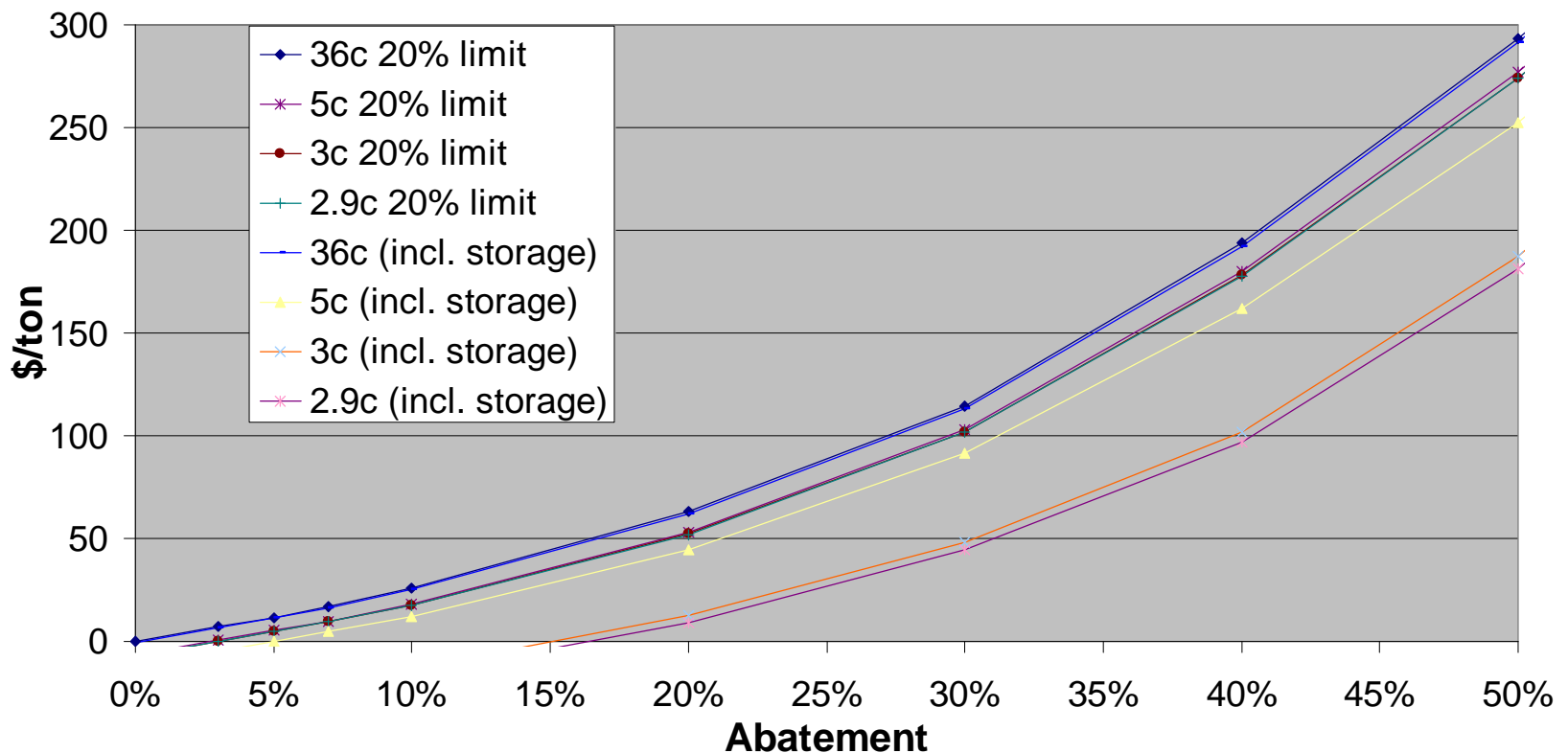
Impact of solar on the MAC: With free storage

Marginal Cost of Abatement

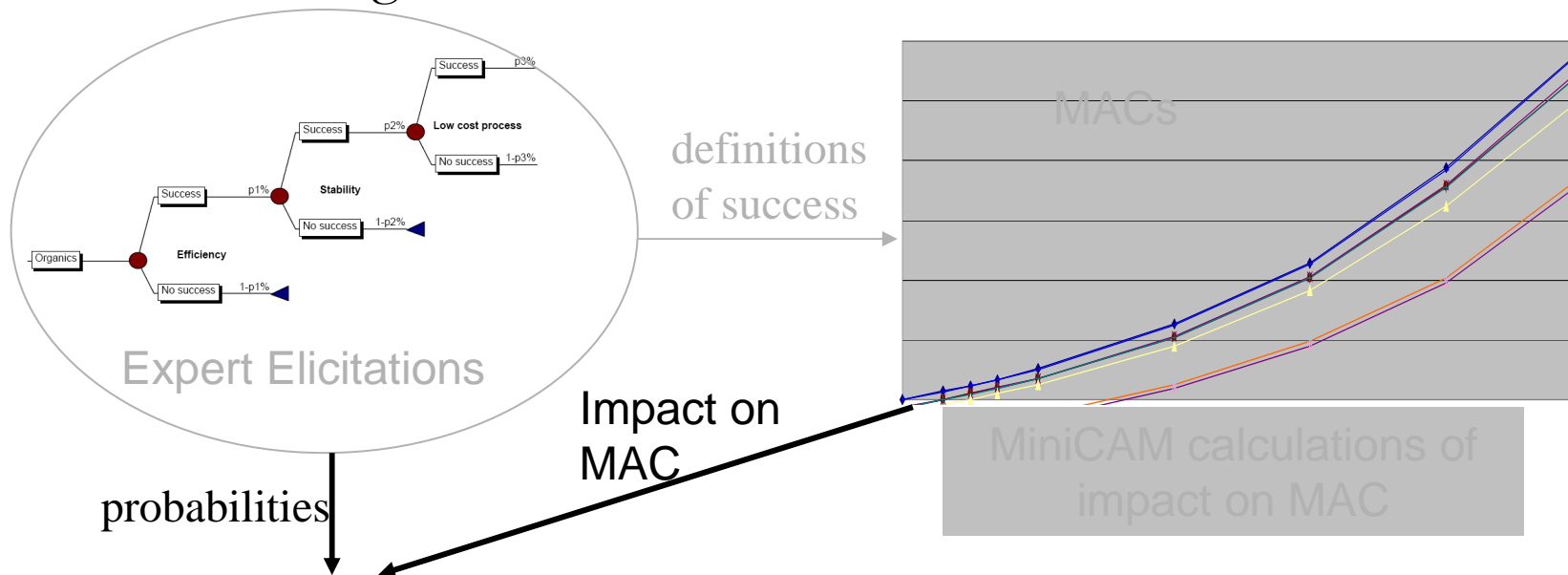


The combination of low cost storage and a breakthrough in solar costs has a significant impact

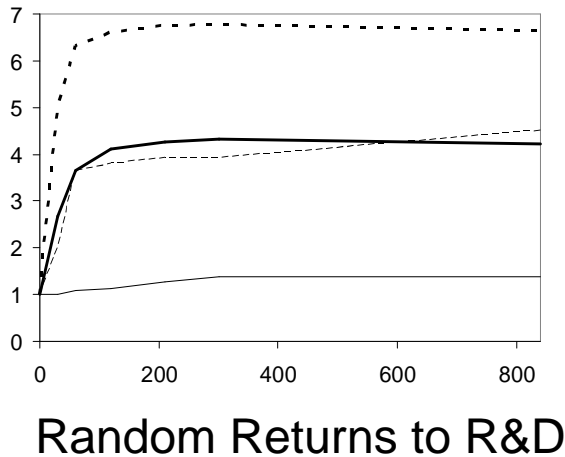
Marginal Cost of Abatement



We are combining expert elicitations with MiniCAM to derive random Marginal Abatement Cost curves



probabilities



- Collect Expert Assessments of Potential R&D Projects
- Determine Impact on MAC, using MiniCAM
- **Develop portable representations of the probabilistic impact of technical change.**

Representing the Impact on the MAC

- We estimate a kind of sufficient statistic to represent the impact of technical change on the MAC
- We propose that the impact of solar can be modeled as follows:

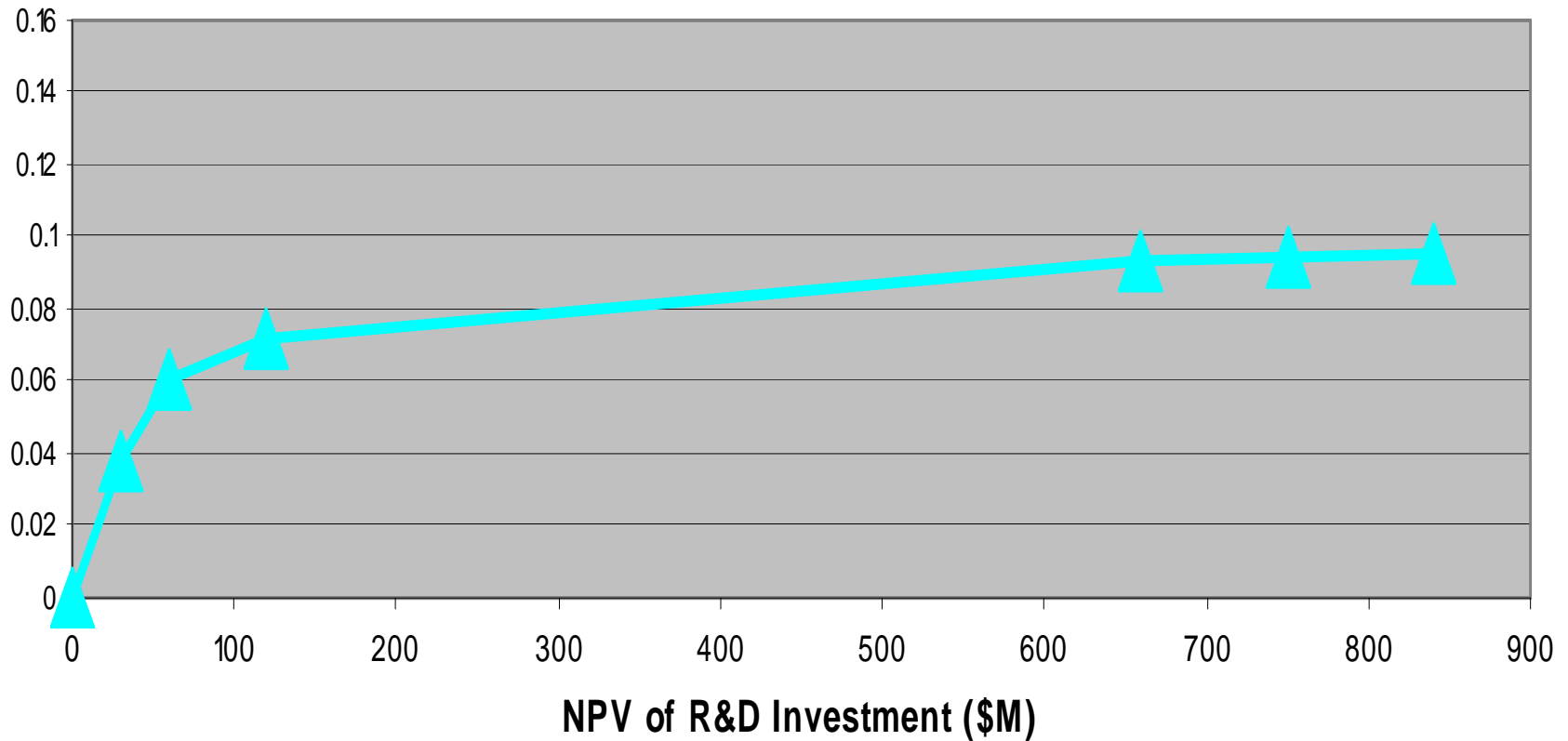
$$MC(\mu; \alpha) = MC(\mu) \left[1 + \alpha(\ln \mu + k) \right]$$

Scenario (cents/kWh)	0.26	0.10	0.05	0.03	0.029
Efficiency Multiplier	1.4	3.6	7.2	12	12.4
Alpha	0.0061	0.0493	0.1418	0.1666	0.1690

Table 2: Statistics for selected success levels

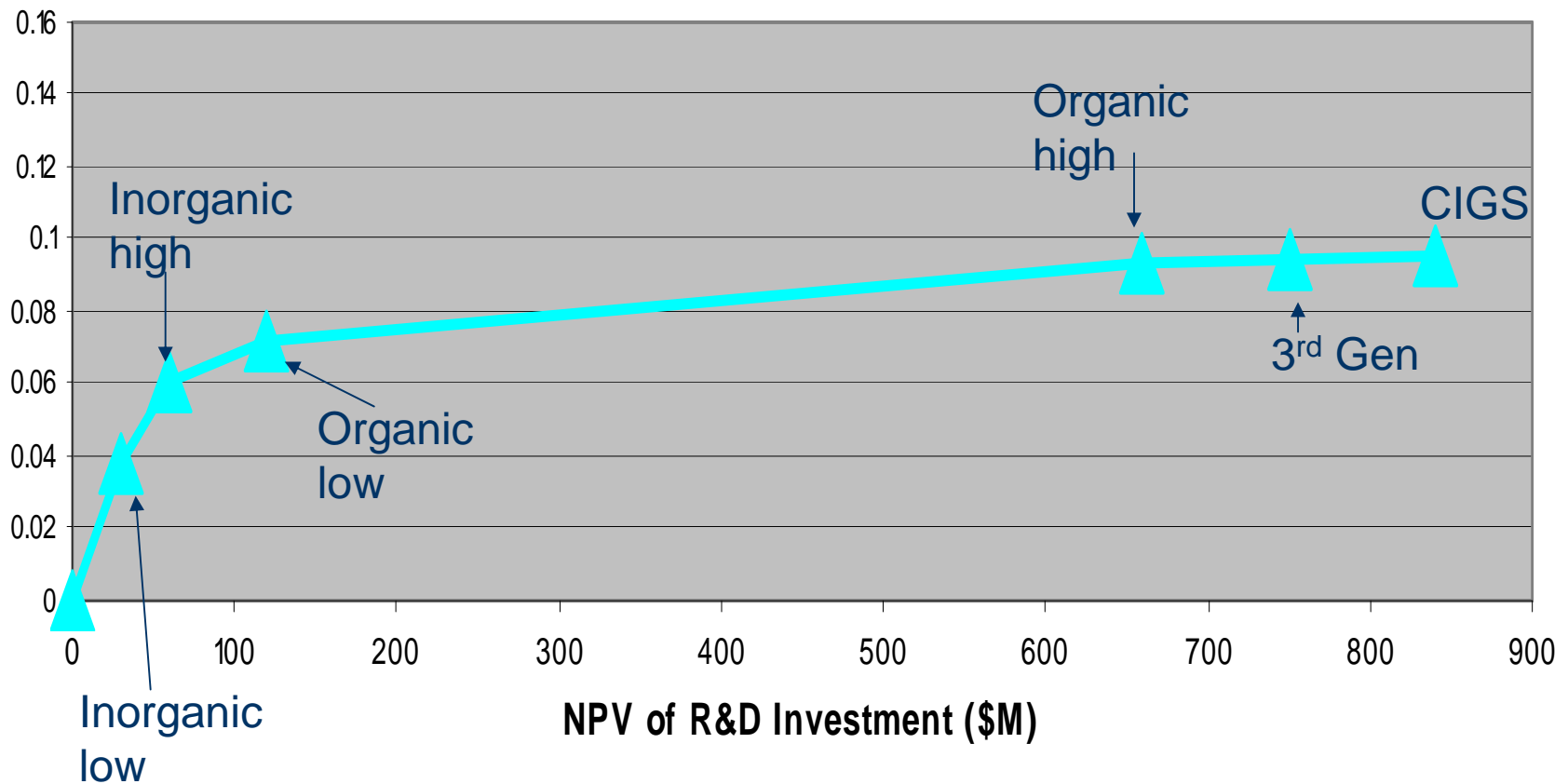
Expected Returns to R&D

Impact on the MAC

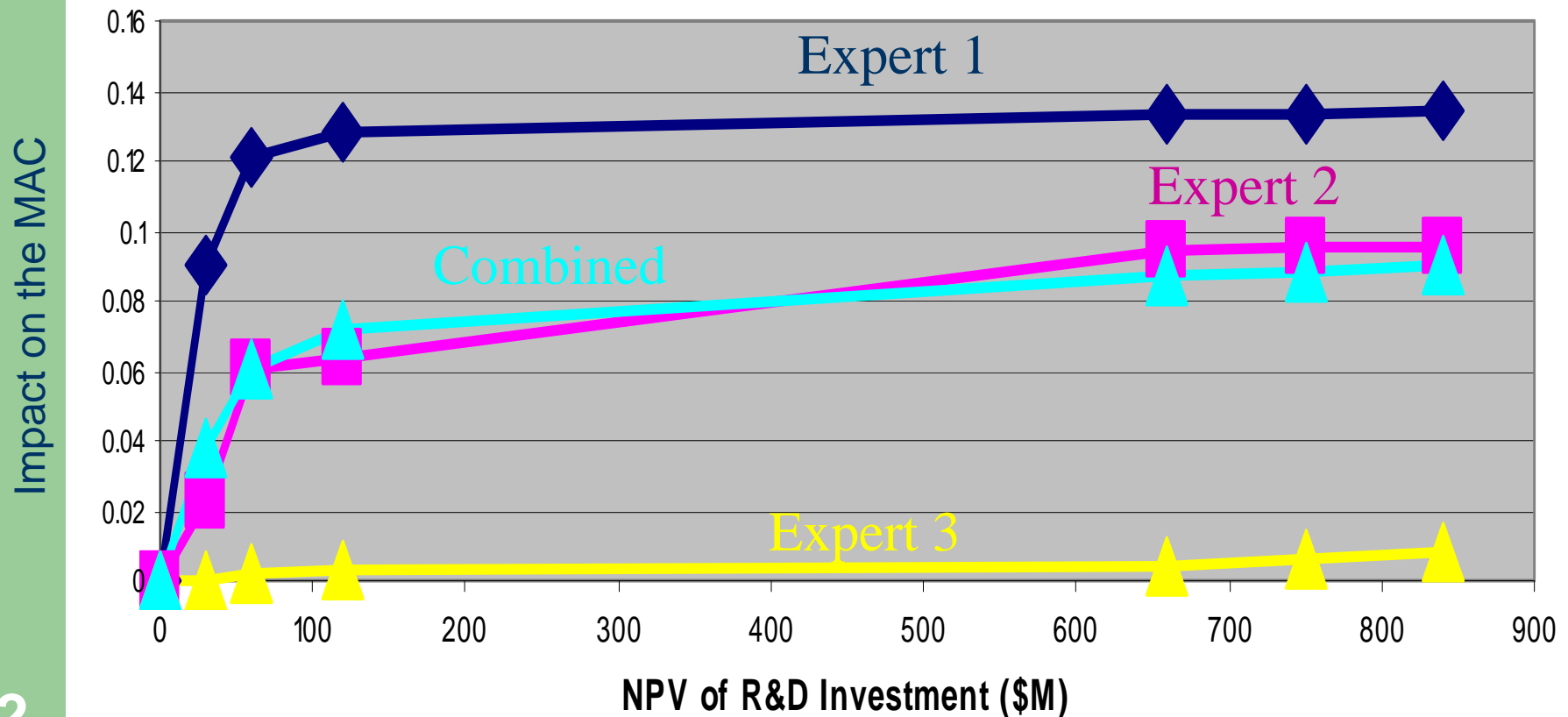


Expected Returns to R&D

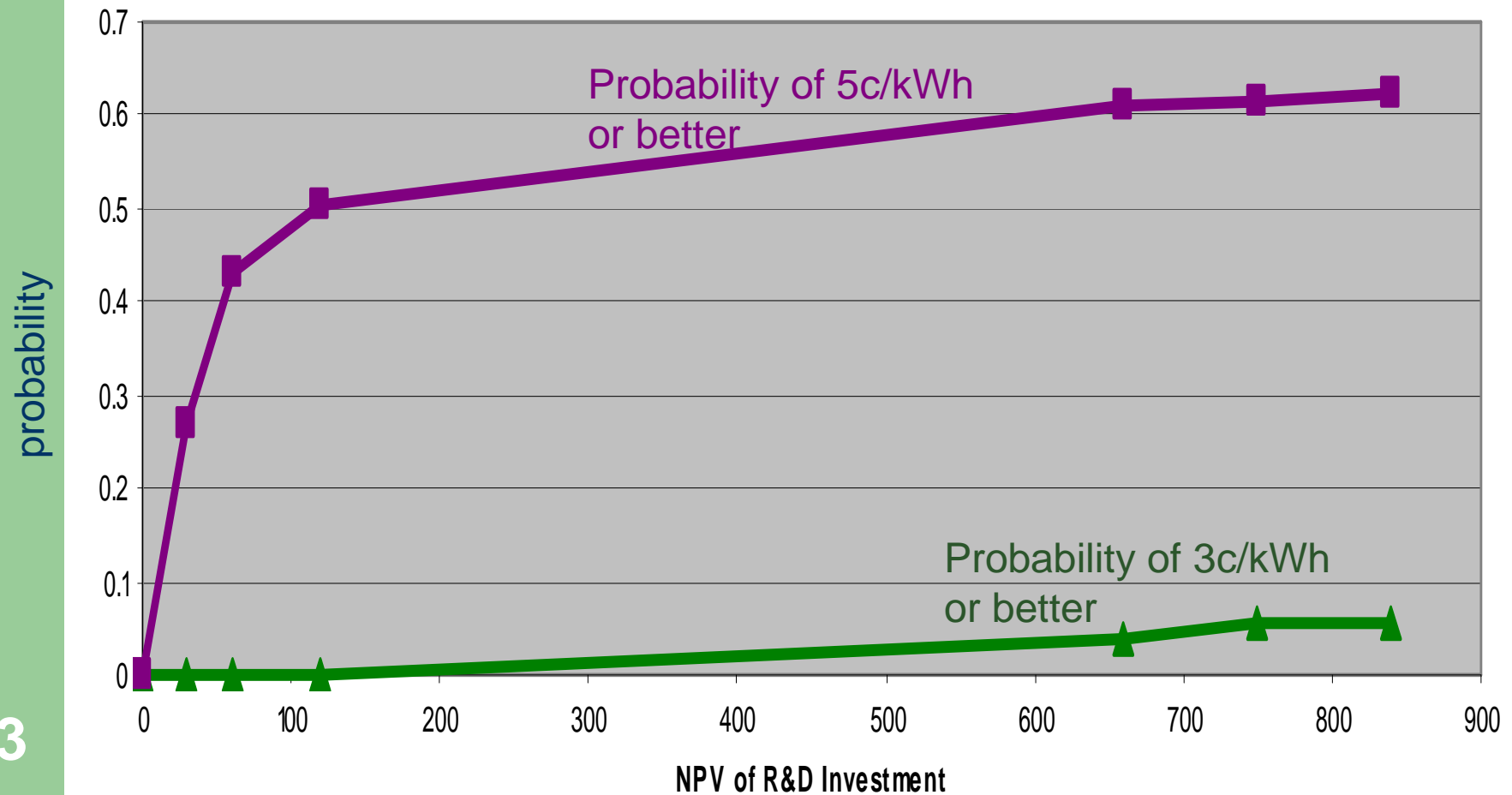
Impact on the MAC



One way to include uncertainty is to assign a probability to each expert



Probability of Success as a function of investment

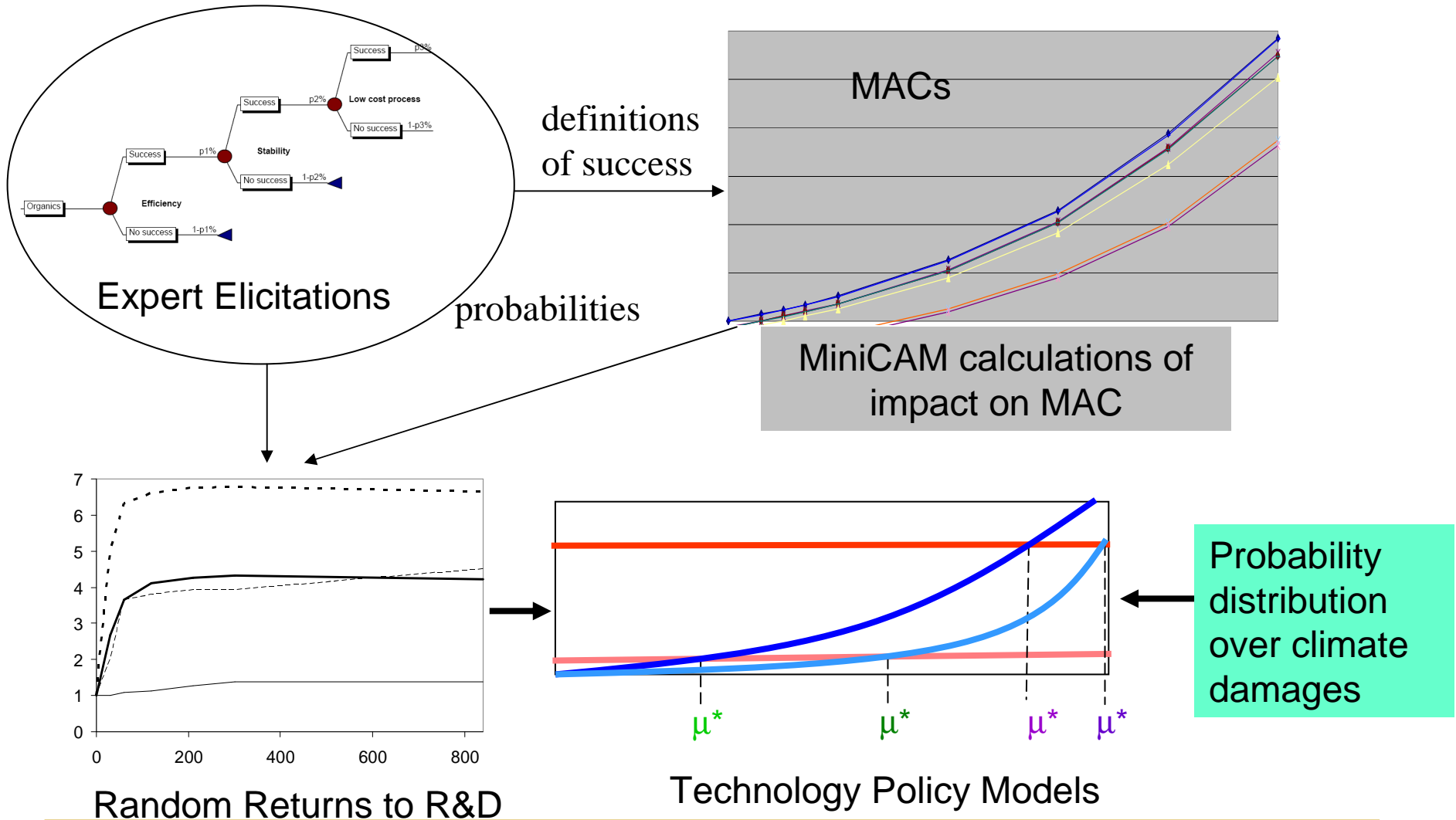


We are working on similar representations for multiple technologies

Advanced Solar PVs
Carbon Capture and Storage & Combustion
Nuclear Fission
Bio-electricity
Wind and Solar Grid Integration
Biofuels
Batteries

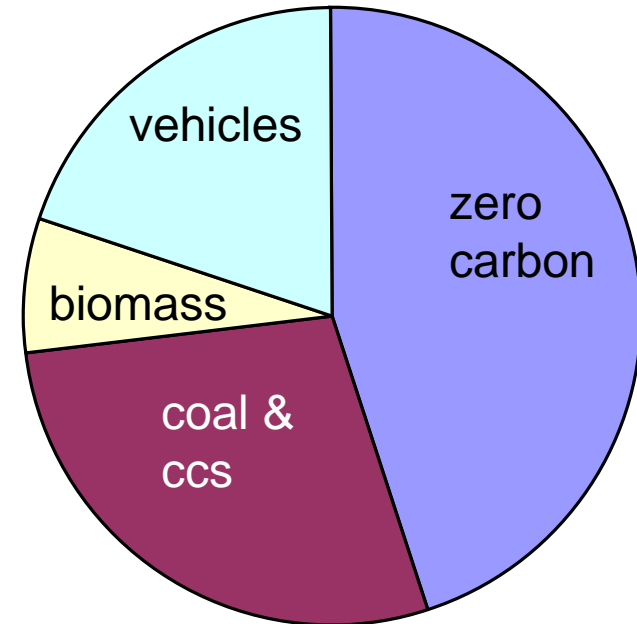
Future Work

Random Marginal Abatement Cost curves can be combined with random damages in Technology Policy Models.



Implementing the data into policy models

- Implement data in DICE and in a DA R&D Model
 - What are the interactions between individual technologies?
 - How does increasing risk in damages interact with the optimal portfolio of technologies?
 - In which categories are riskier technologies more attractive than incremental technologies?
 - What is impact on optimal abatement of having a portfolio of technologies available?
 - What is impact on optimal abatement of riskiness of portfolio available?
 - Are some portfolios robust, in that they are almost optimal for a wide variety of damage probabilities?
 - Value of better information on technical success?



?

How does this analysis compare to other climate change policy analyses?

- We are taking a portfolio approach to analyzing climate change technology policy.
- We will be able to incorporate uncertainty in both climate damages and in technical change.
- Our representation of technical change is data-driven
 - At this point very little is understood about how technical change will impact the abatement cost curve; nor about the returns to R&D

Conclusion

- Modeling uncertainty is important for near-term technology policy.
 - Different types of technical change have different implications
- Expert Elicitations provide data for uncertainty analysis.
 - Integrating expert elicitations with case studies and econometric data is a promising avenue for improving the empirical basis of uncertainty analysis.
- We are integrating multiple modeling paradigms to analyze this problem.
 - A number of frameworks for integrating IAMs with uncertainty analysis are currently being developed.

This research is partially supported by the Office of Science (BER) U.S. Department of Energy, Grant No.DE-FG02-06ER64203. With Leon Clarke, Jeff Keisler, Matthias Ruth, Detlof von Winterfeldt, and John Weyant.