CLIMATE CHANGE POLICY UNDER UNCERTAINTY

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European Summer School on Uncertainty, Innovation, and Climate Change

Lecture I

Objectives

- Understand why we model uncertainty (from decision-centric point of view)
- Discuss concepts of *objective* vs *subjective* uncertainty, and *risk* vs *uncertainty*

- Understand the basics of the comparative statics of uncertainty and learning
- Apply this to climate change problem

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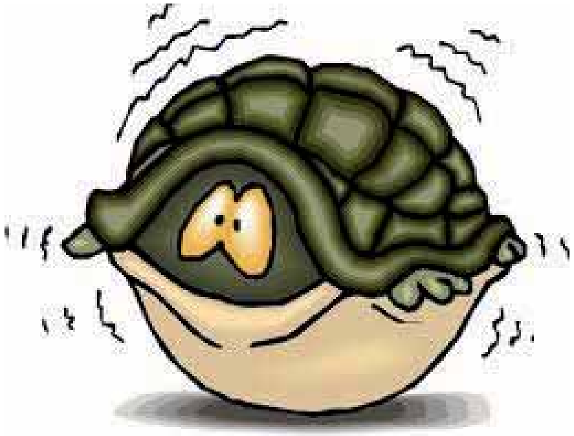
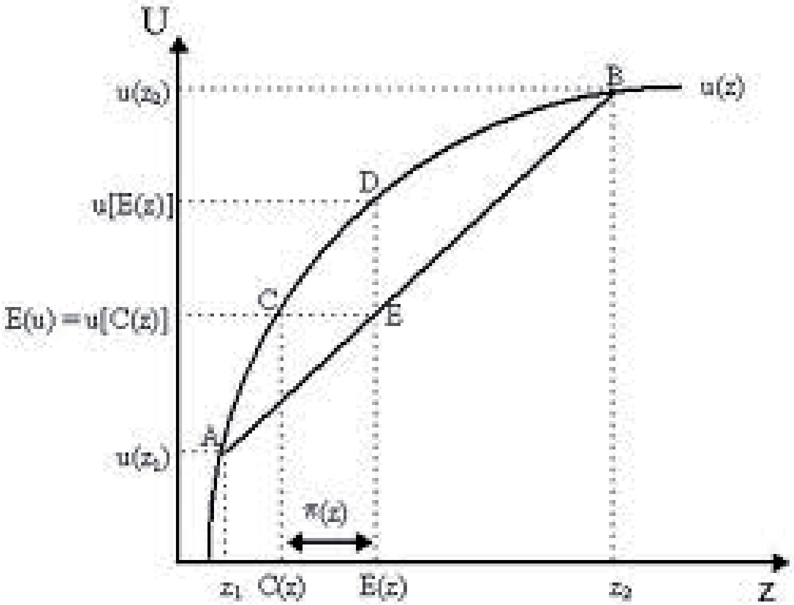
- Discuss the role of technology
- Overview of lit on CC, technology, and uncertainty

Uncertainty and decision making

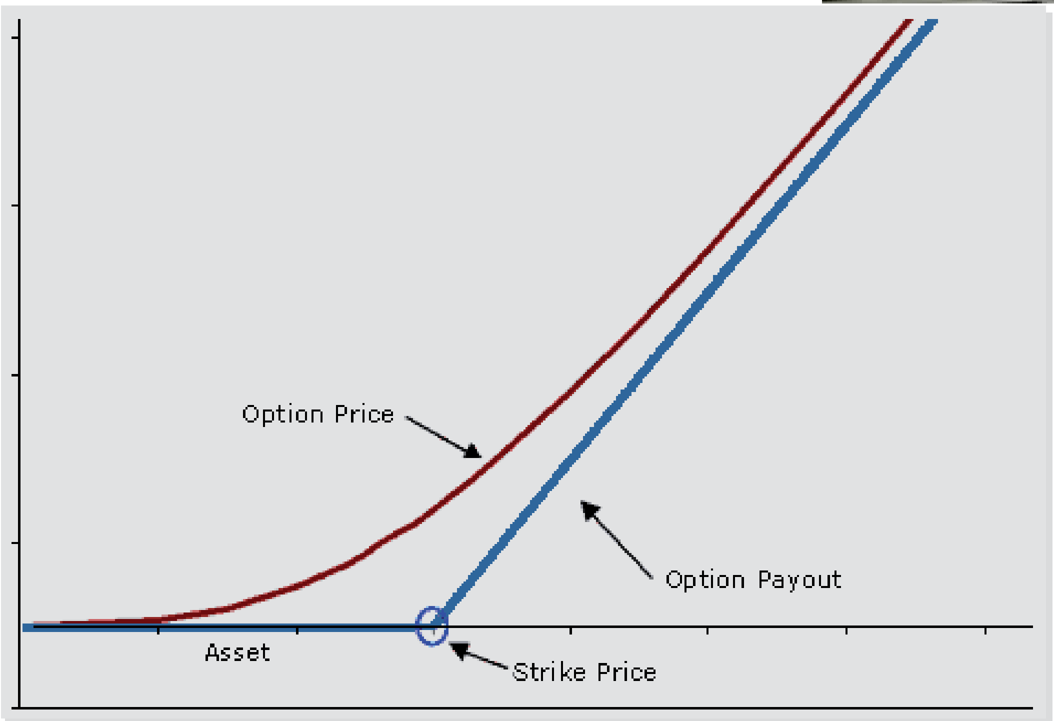
- Why should we incorporate uncertainty?

Risk Aversion





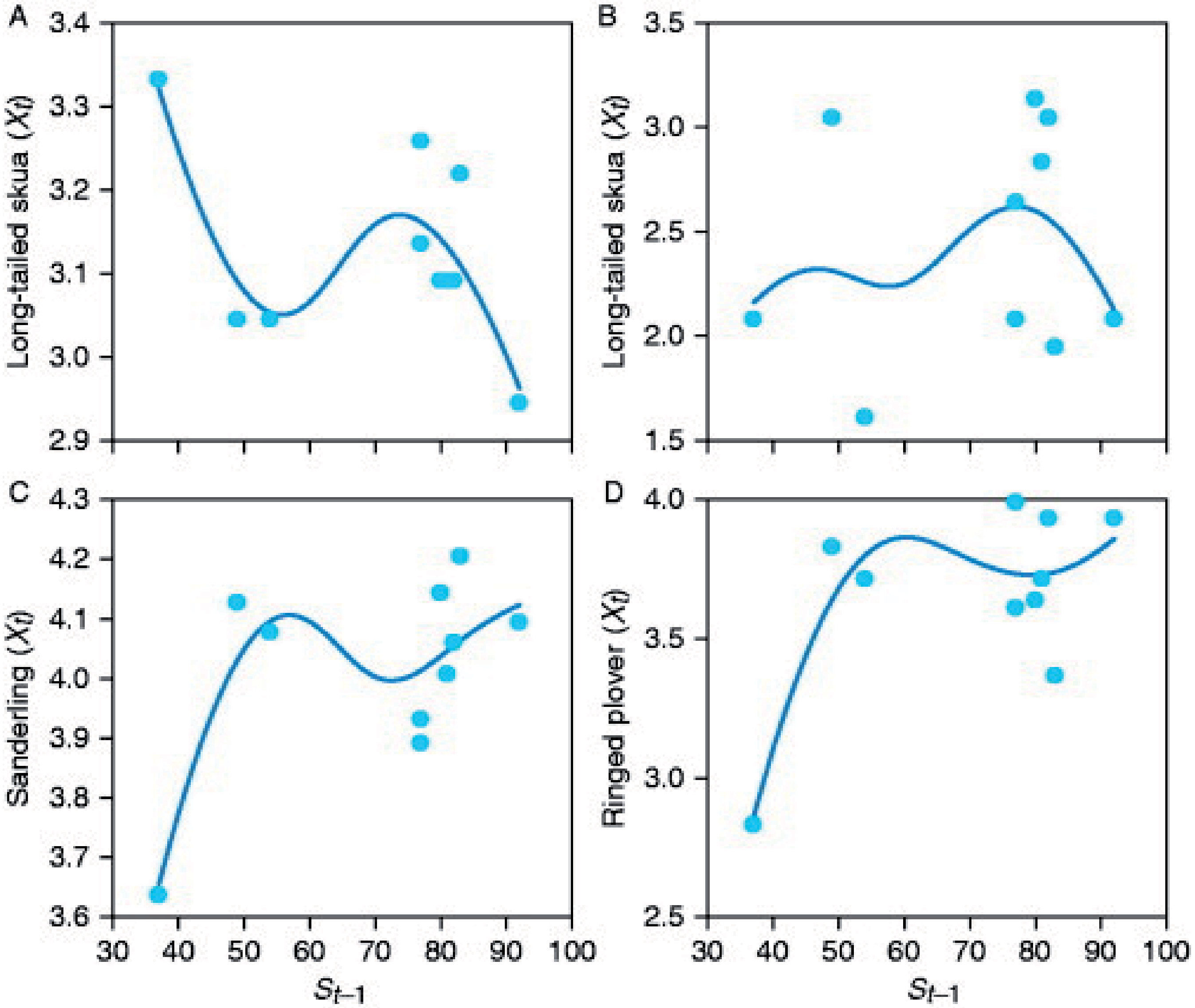
Options



The flaw of averages

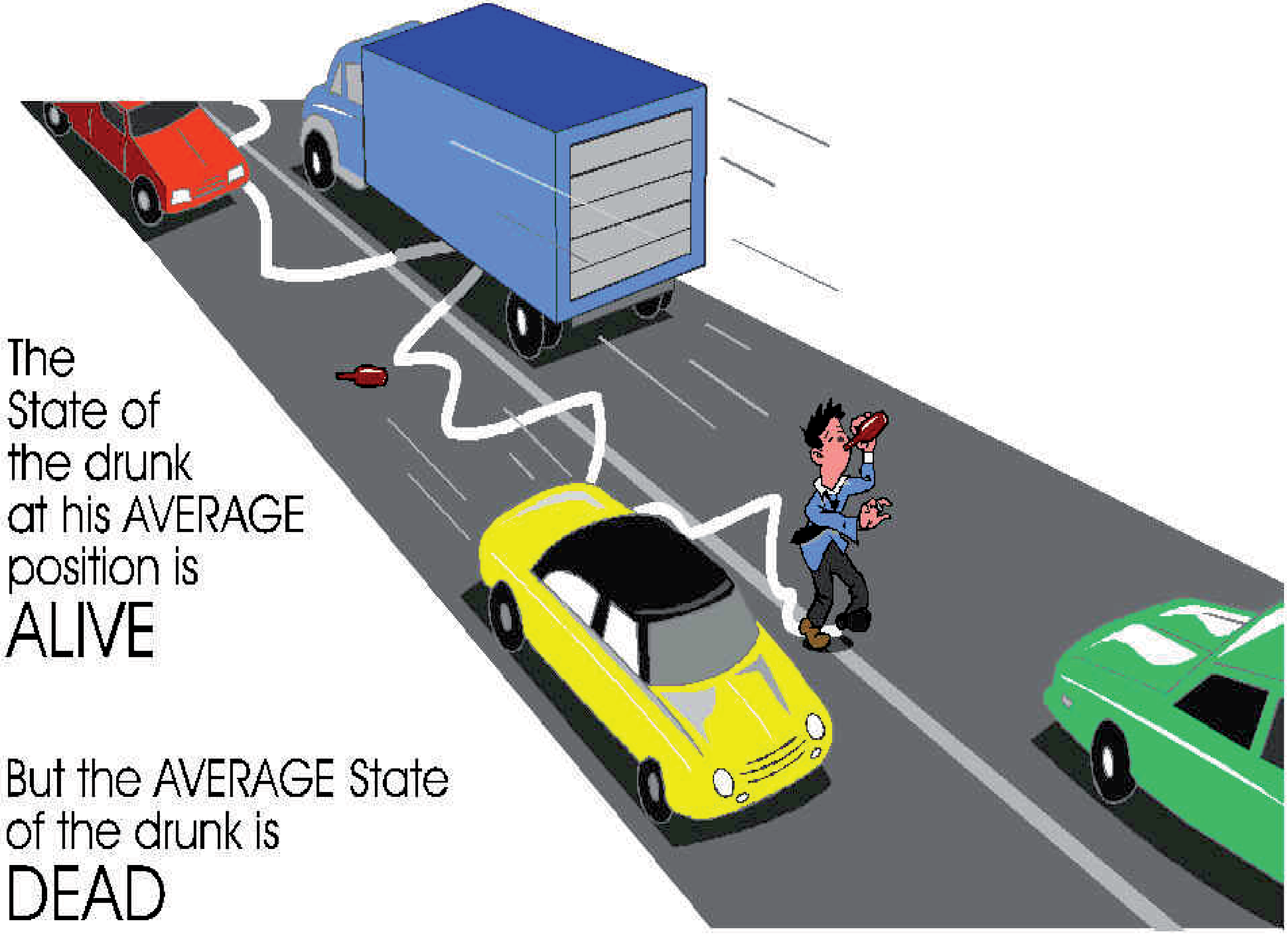
- The Flaw of Averages:
  - A function of the expected value is not equal to the expected value of the function, unless the function is linear.

$$E\left[f(x)\right] \neq f\left(E[x]\right)$$



A sobering example of the Flaw of Averages

(taken from Sam Savage's Insight.xla)



$$E\left[f(x)\right] \neq f\left(E[x]\right)$$

Uncertainty and decision making

- Why should we incorporate uncertainty?
  - Risk aversion
  - Options
  - The Flaw of Averages
- What do all of these have in common?

Uncertainty and decision making

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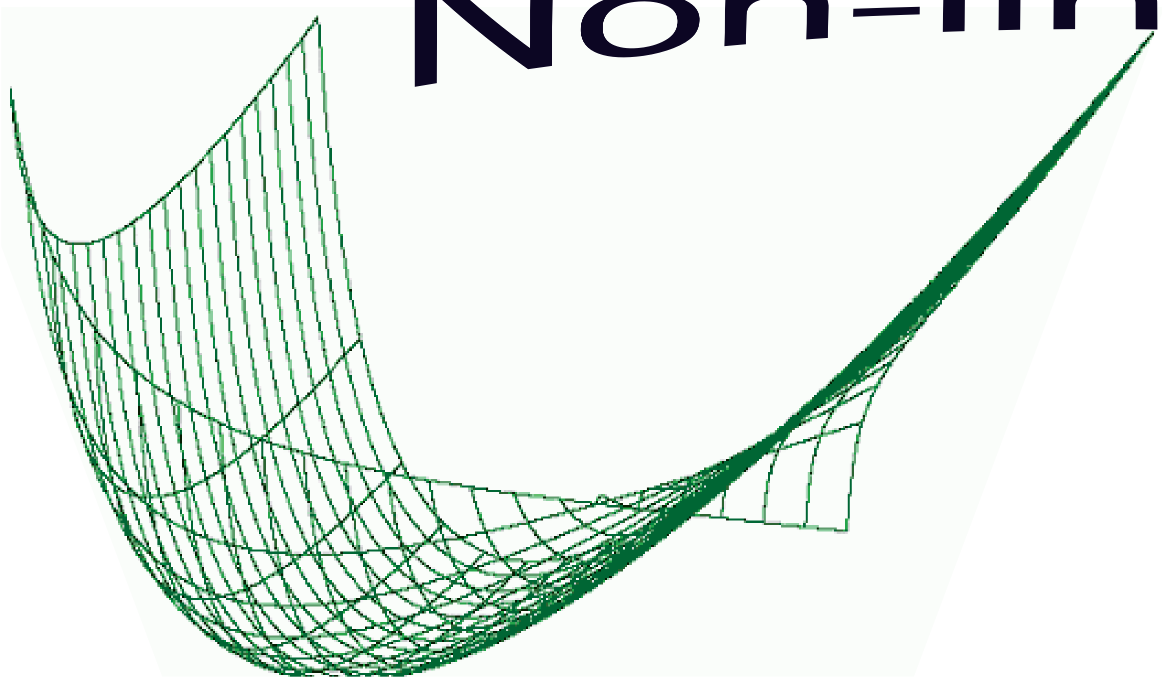
Non-linearity



Subjective vs. Objective Probability

- Objective probabilities are usually related to events which happen frequently. The frequency is taken to be the probability.

- Subjective probabilities are usually related to events which occur infrequently.

Is there a well-defined distinction?

Subjective vs. Objective Probability

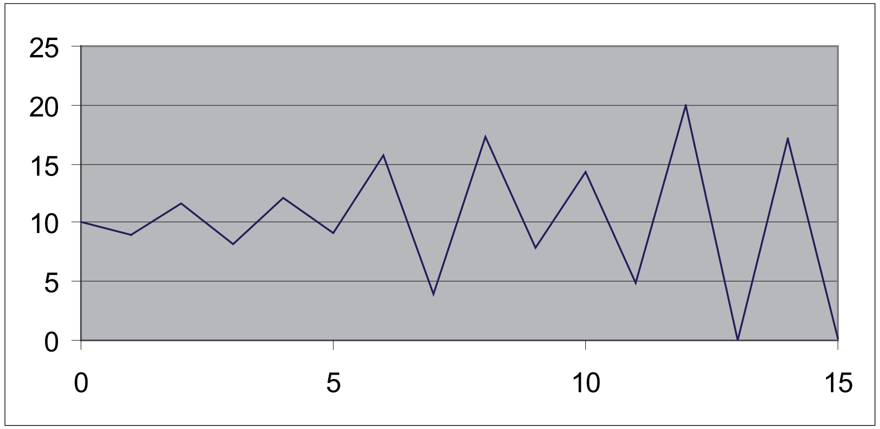
- Objective probabilities are usually related to events which happen frequently. The frequency is taken to be the probability.  
- Subjective probabilities are usually related to events which occur infrequently. 
- Really, both kinds of probabilities simply reflect beliefs.
- You can assign a probability distribution to anything that you don’t know. A random variable does not have reflect a value that fluctuates.

“risk” vs “uncertainty”

- **A distinction?**
  - **risk** is present when future events occur with measurable probability
  - **uncertainty** is present when the likelihood of future events is indefinite or incalculable

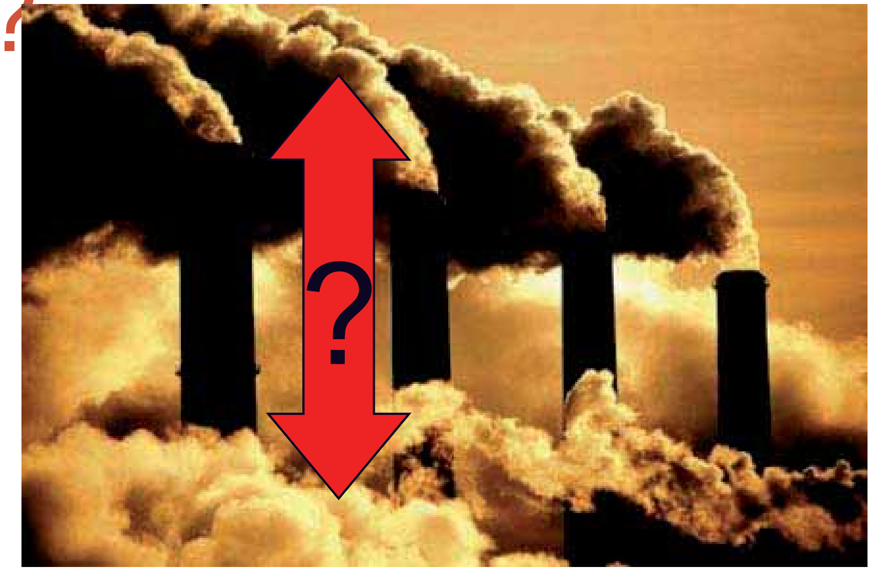
STOCHASTIC DOMINANCE AND THE COMPARATIVE STATICS OF UNCERTAINTY AND LEARNING

How does Uncertainty and Learning impact optimal climate change policy?

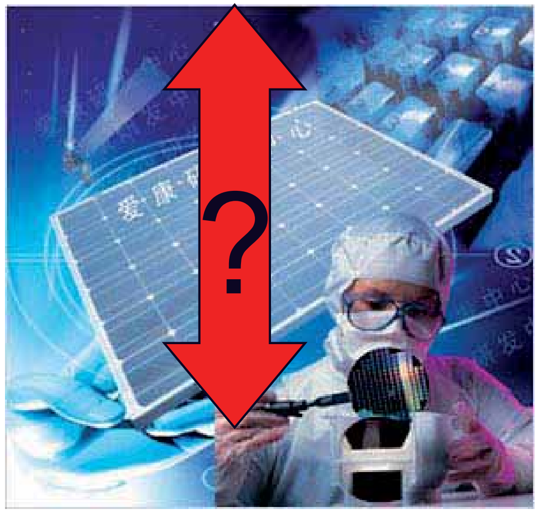


Increasing risk in climate damages

An increase in the amount we expect to learn



Do optimal emissions increase or decrease?



Does optimal R&D increase or decrease?

Define "Riskier"

- What does it mean for one random variable to be riskier or more uncertain than another?

Define Riskier

What does it mean for one random variable x to be riskier than another y?

1. All risk averters prefer y to x

   Eu(y)>Eu(x) for all concave u( )

Define Riskier

What does it mean for one random variable x to be riskier than another y?

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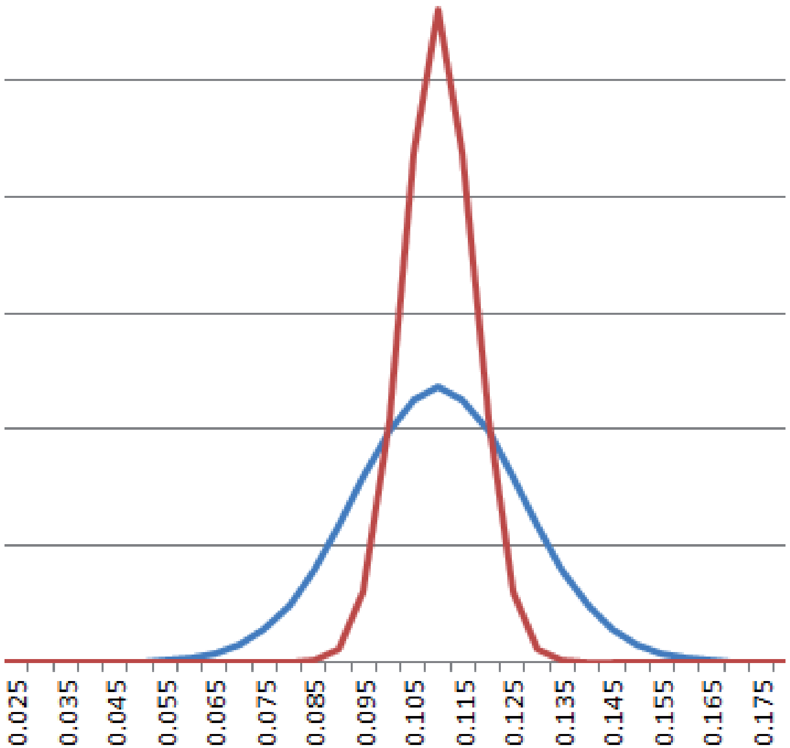
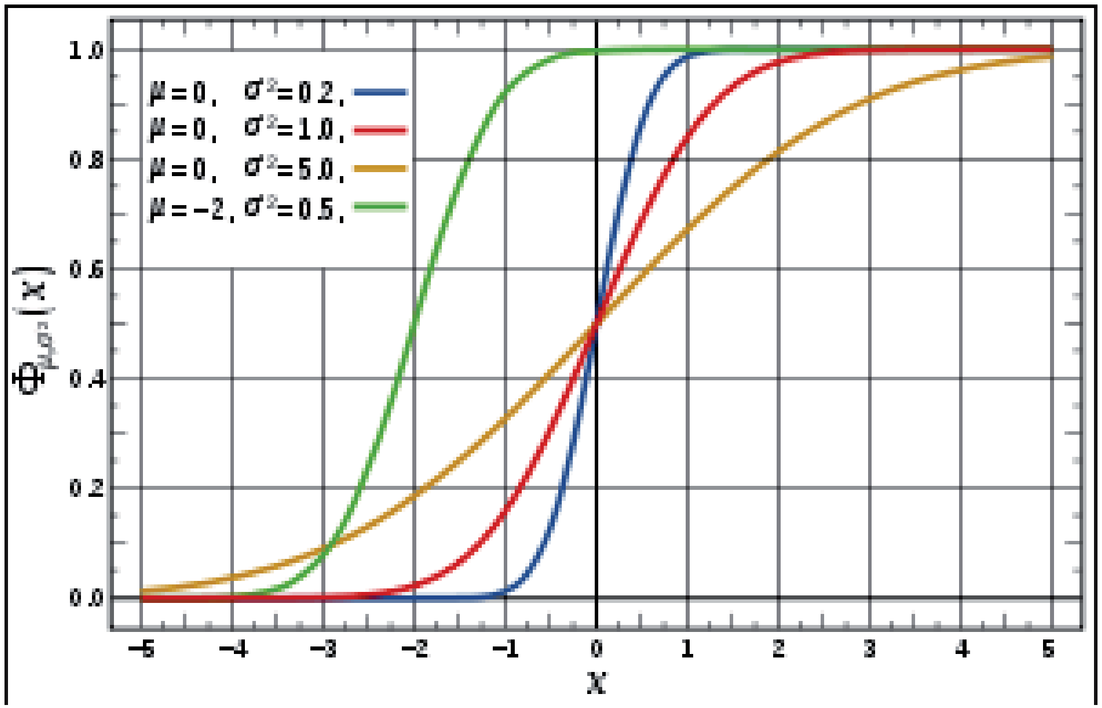
2. The distribution G has more weight in the tails than the distribution F.

   - A mean preserving spread

$$\int_{y}\left[F(x)-G(x)\right]dx \le 0 \quad \forall y$$





Define Riskier

What does it mean for one random variable x to be riskier than another y?

1. All risk averters prefer y to x

   Eu(y)>Eu(x) for all concave u( )

2. The distribution of x has more weight in the tails than the distribution of y.
   - A mean preserving spread

3. x has the same distribution as y, with extra noise added.

4. x has a larger variance than y.

- Which one of these things is not like the other?

Define Riskier

What does it mean for one random variable x to be riskier than another y?

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- 1. and 2. and 3. are equivalent. 4. is not.

i.e. x may have a larger variance than y, yet some risk averters will prefer it.

Define Riskier

1. All risk averters prefer y to x

   Eu(y)>Eu(x) for all concave u( )
2. The distribution of x has more weight in the tails than the distribution of y.
3. x has the same distribution as y, with extra noise added.

- This is called a Mean-Preserving Spread.
- Point 1 means that if x is riskier than y, then E[g(y)] > E[g(x)] for all concave functions g().

Implication

- Point 1 means that if *x is riskier than y*, then

  $E[g(y)] > E[g(x)]$ for *all concave functions g()*.
- The expected value of a function of a random variable is *increasing in risk* if and only if the function is *convex*.
- It is *decreasing in risk* if and only if the function is *concave*.
- If the function is neither convex nor concave, it will increase with some increases in risk and decrease with other decreases in risk.

Other definitions of increasing risk

- First order stochastic dominance: Eu(y)>Eu(x) for all increasing u( )
- Second order stochastic dominance Eu(y)>Eu(x) for all increasing, concave u( )
- Third order stochastic dominance Eu(y)>Eu(x) for all increasing, concave u'''()>0
- Each of these definitions can be represented in terms of the distributions.
- There is also some recent work, inspired by prospect theory, considering increasing S-shaped and reverse S-shaped functions (Levy and Wiener 1998)

Stochastic Dominance theory has been applied to decision theory for about 50 years (see Levy 1992, for a review).

Optimal Decision

- Consider the generic decision problem:

$$\max_{x} E_z\left[b(x;z)\right]-c(x)$$

- It is maximized when expected marginal benefits equals expected marginal costs.

$$E_z\left[\frac{\partial b(x;z)}{\partial x}\right]=c'(x)$$

Optimal Decision

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Assume that x* increases as the LHS increases. Then, x* increases in risk if

$\dfrac{\partial b(x;z)}{\partial x}$ is convex in z; x* decreases in risk if the partial is concave; and it is ambiguous if the partial is neither convex nor concave

Optimal Decision

- Consider the generic 2-period decision problem with learning:

$$\max_{x_1} E_z\left[\max_{x_2} b\left(x_1, x_2; z\right) - c_2\left(x_2\right)\right] - c_1\left(x_1\right)$$

- It is maximized when expected marginal benefits equals expected marginal costs. The partial of b will not be linear

$$E_z\left[\frac{\partial b\left(x_1, x_2^*; z\right)}{\partial x_1}\right] = c_1'\left(x_1\right)$$

Definitions

- Increasing Risk, Uncertainty, MPS
  - Z is riskier than Z′ iff

    for all concave U

$$E_Z\left[U\left(Z\right)\right] \leq E_{Z'}\left[U\left(Z'\right)\right]$$

- Y is more informative than Y' if

$$E_Y\left\{\max_{x_1} E_{Z|Y} \max_{x_2}\left[U\left(x_1, x_2, Z\right)\right]\right\} \geq$$

for all U.

$$E_{Y'}\left\{\max_{x_1} E_{Z|Y'} \max_{x_2}\left[U\left(x_1, x_2, Z\right)\right]\right\}$$

Optimal Decision

- Consider the generic 2-period decision problem with partial learning:

$$\max_{x_1} E_Y\left[\max_{x_2} E_{Z|Y}\left[b\left(x_1, x_2; Z\right) - c_2\left(x_2\right)\right]\right] - c_1\left(x_1\right)$$

$$B\left(x_1, F_{Z|Y}\right) \equiv \max_{x_2} E_{Z|Y}\left[b\left(x_1, x_2; Z\right) - c_2\left(x_2\right)\right]$$

$$E_z\left[\frac{\partial B}{\partial x_1}\right] = c'\left(x_1\right)$$

Theorem

$$x_1{}^* = \arg\max_{x_1} E_Y \max_{x_2} E_{Z|Y}\left[U\left(x_1, x_2, Z\right)\right]$$

$$x_1{}^{**} = \arg\max_{x_1} E_Z \max_{x_2}\left[U\left(x_1, x_2, Z\right)\right]$$

If U is linear (or separable) in Z, then:

x_1* increases in informativeness iff

x_1** increases in risk

CLIMATE CHANGE AND STOCHASTIC DOMINANCE

Climate Change Model

$$\min_{\mu} c(\mu) + \delta E_z \left[\min_{\mu_2} c(\mu_2) + D(S - \mu - \mu_2; z) \right]$$

μ Abatement

δ discount factor

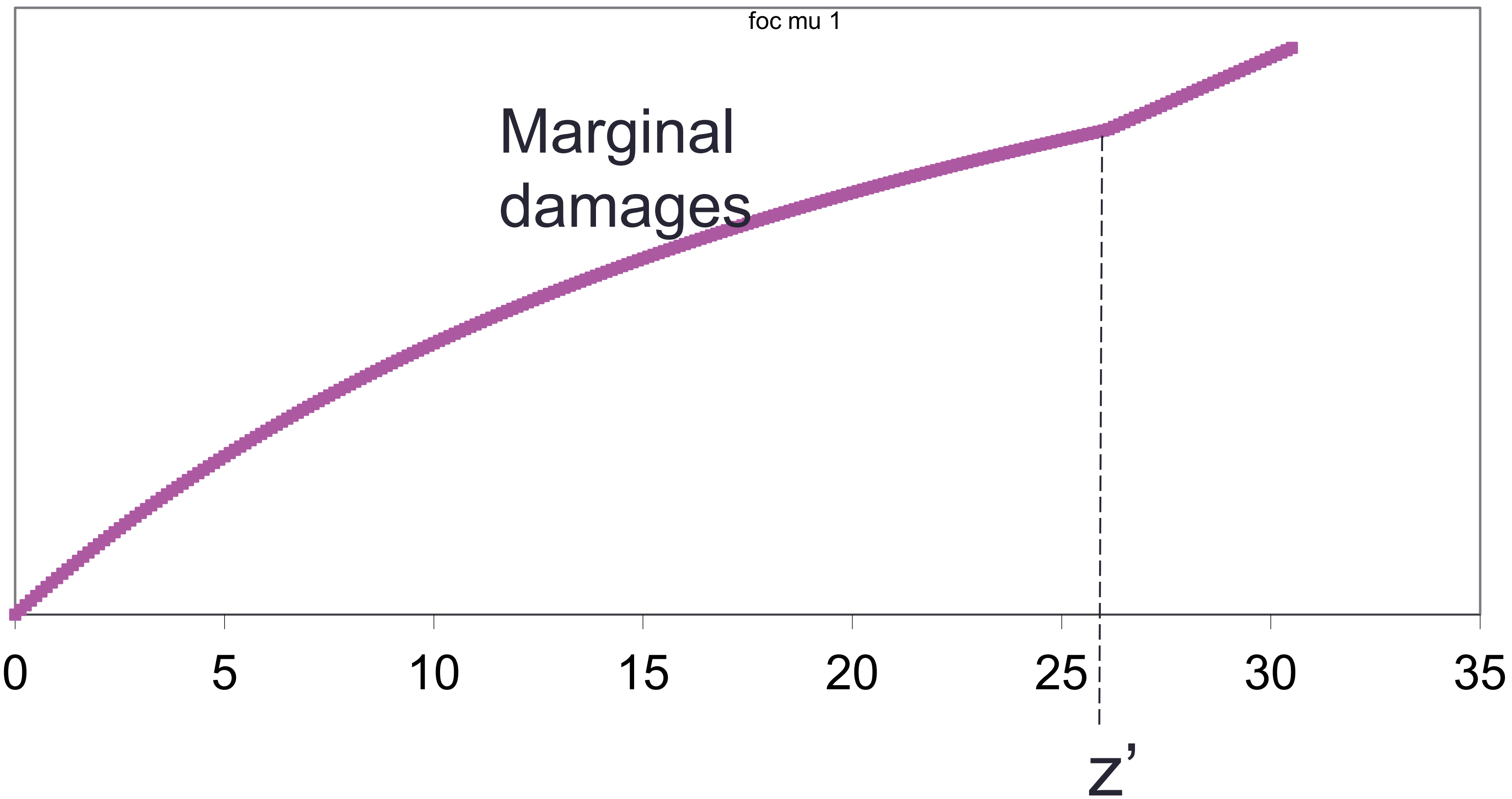
S BAU stock of emissions

z uncertainty about damages

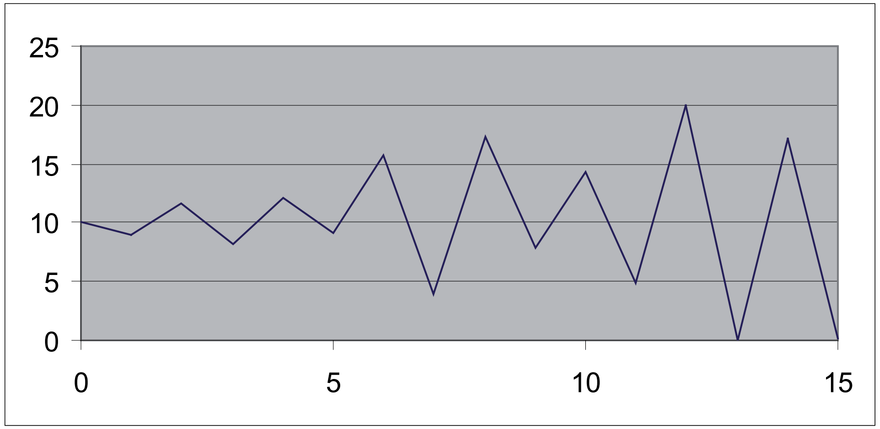
Climate Change Model

The marginal benefits from abatement are set equal to the marginal damages from one more unit of emissions

$$c'(\mu) = E_z\left[MD\left(S-\mu-\mu^*{}_2;z\right)\right]$$

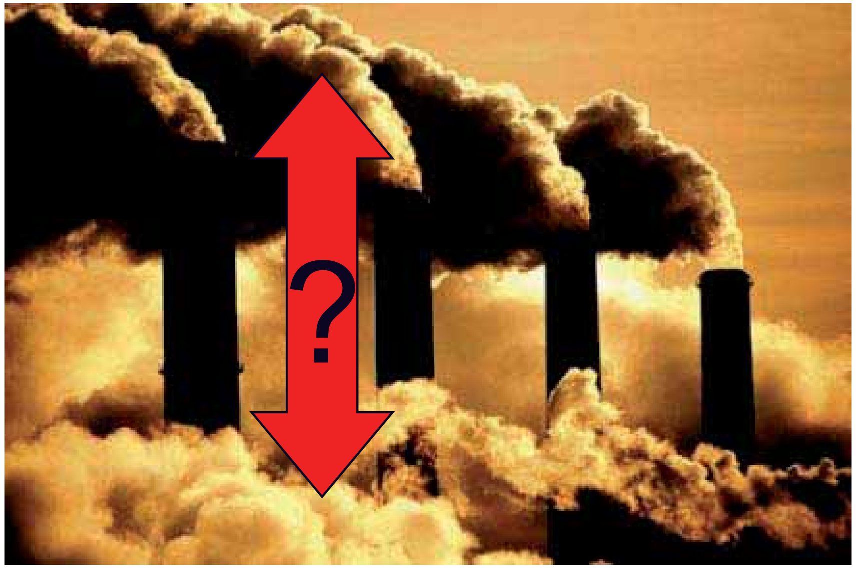


How does Uncertainty and Learning impact optimal climate change policy?



Increasing risk in climate damages

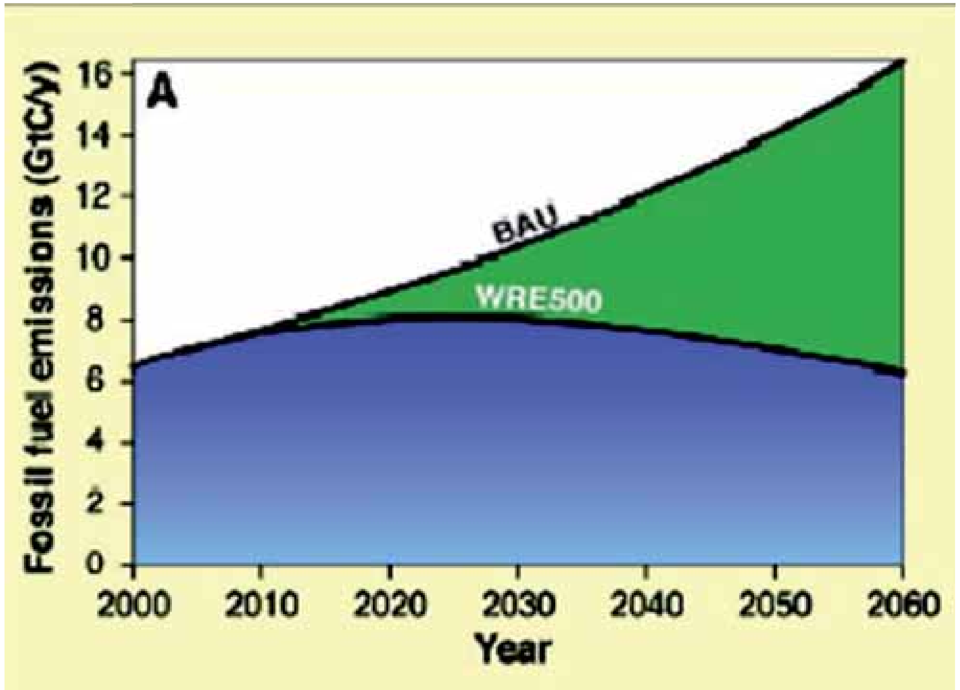
An increase in the amount we expect to learn



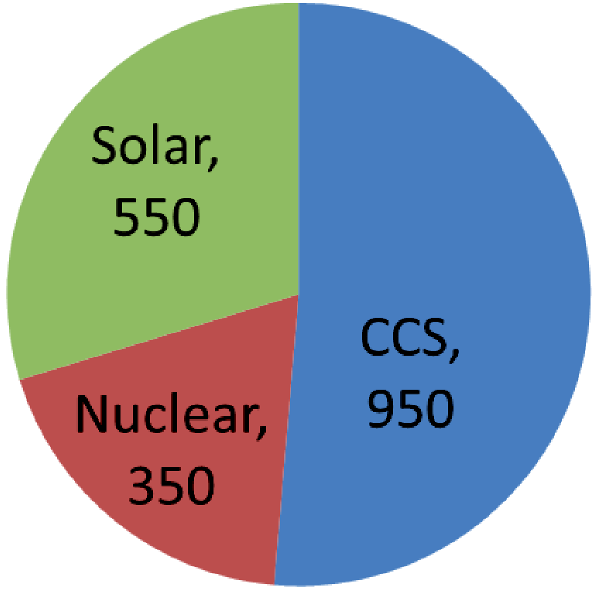
Optimal emissions may increase or decrease: It depends on the specific increase in risk or increase in informativeness

THE ROLE OF TECHNICAL CHANGE

What to do about climate change?



What is the optimal path for a carbon tax and/or an emissions path?



What is the optimal portfolio of technology policies?

Is technology R&D a hedge against climate uncertainty?

Approaches to modeling technical change in top-down models

Impacts to MAC	Impacts to Cost of Abatement	Emissions -Output ratio	Production Function	Profit Function
■Fischer, Parry, & Pizer (2003) ■ Goulder & Schneider(1999) ■Jung et al (1996) ■Milliman & Prince(1989)	■Baker et al (2006ab) ■Montero (2002) ■ Goulder & Mathai (2000) ■ Parry (1998)	■Gerlagh & vanderZwaan (2006) ■Buonano et al. (2003) ■Nordhaus (2002)	■Popp (2004a&b) ■Goulder & Schneider (1999) ■Farzin & Kort (2000)	Baker&Shittu (2006)

Some Assumptions result in a lower MAC everywhere…

Impacts to MAC	Impacts to Cost of Abatement	Reduce Emissions-Output ratio	Production Function	Profit Function
Assume lower	**Pivots downward; proportional reduction**		**Substitute knowledge for non-fossil inputs***	**Reduce effective price of non-fossil***
	Pivots rightward	Reduce emission/output ratio	Substitute knowledge for fossil inputs	Reduce carbon content of fossil energy

* Depends on parameters of production function

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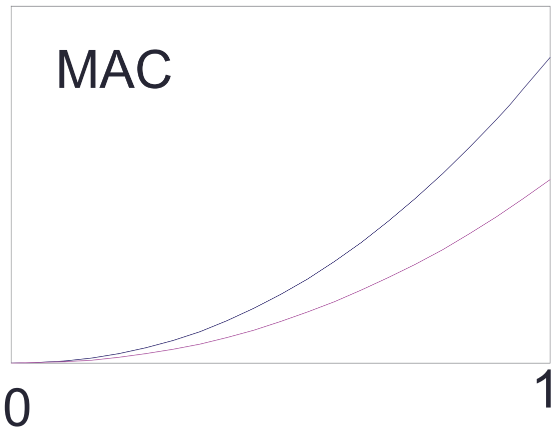

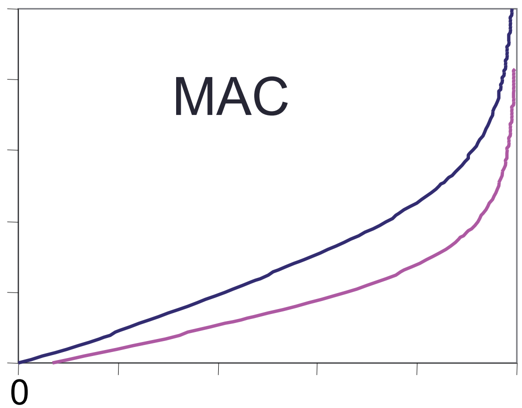

Some Assumptions result in a ***higher*** MAC at high levels of abatement

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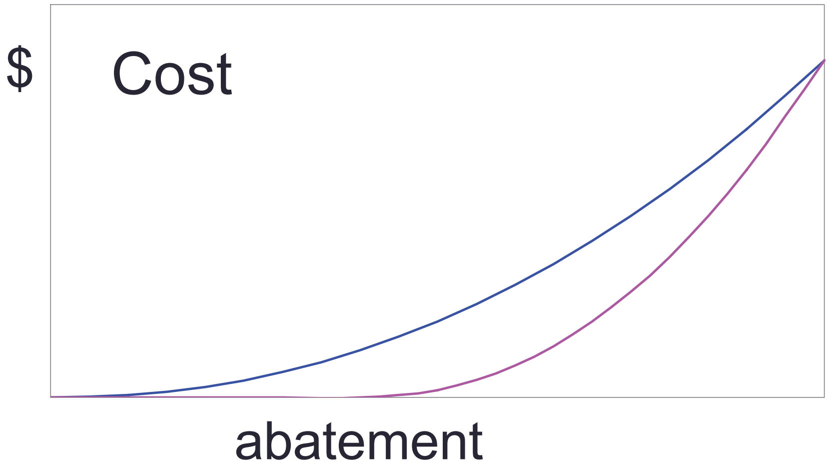
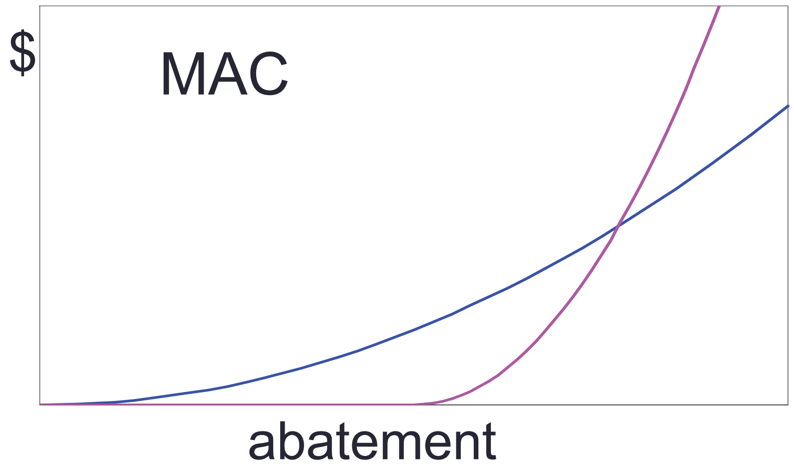
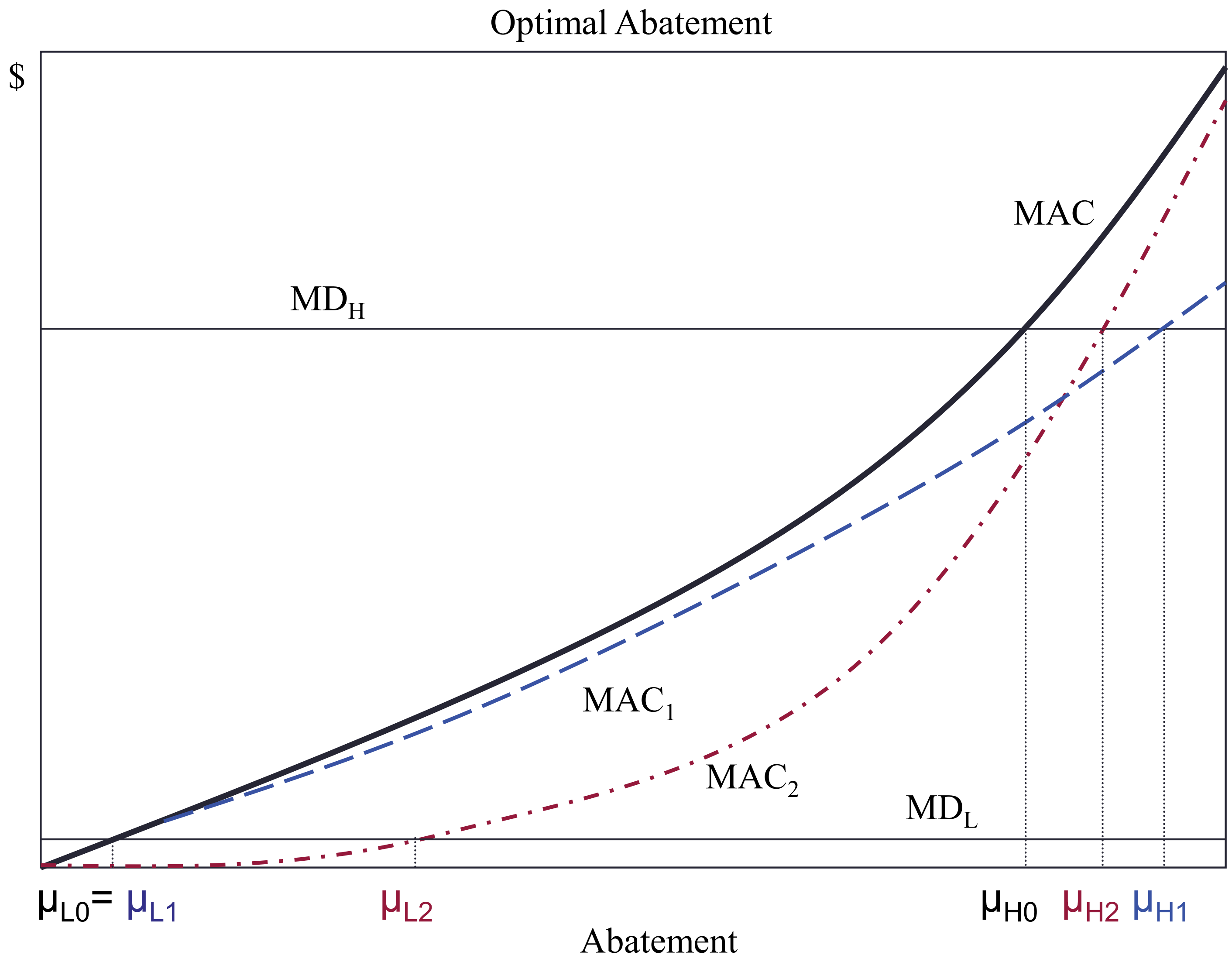




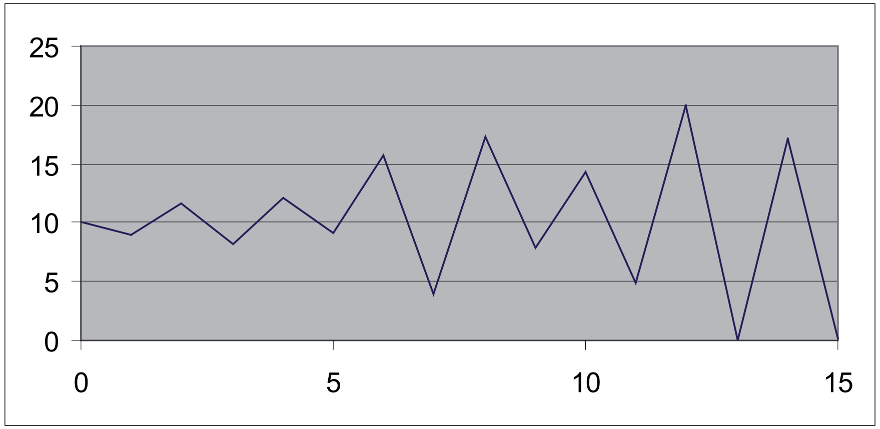
The effect of technical change on optimal abatement depends on the kind of technical change and on the level of damages



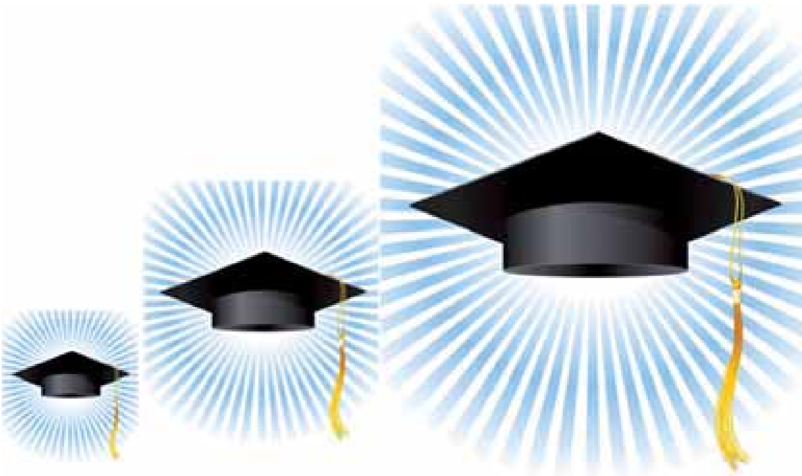
Uncertainty and endogenous technical change

	Uncertainty		
Policy Type	Damages (Carbon Tax)	Technical Change	Damages and Technical Change
Technology Policy	Baker, Clarke & Weyant (2006)	Gritsevskyi& Nakicenovic (2002); Goeschl & Perino (2007); Bosetti&Tavoni (2007); Siddiqui & Fleten (2010); Bosetti & Tavoni (2009); Papathanasiou et al (2001)	Grubler & Gritsevskyi (2002); Blanford & Weyant (2007); Blanford (2009); Baker & Adu-Bonnah(2008); Baker and Solak (2011);
Emissions Policy	Farzin & Kort (2000); Baker & Shittu (2006);	Löschel & Otto (2009)	
Technology and emissions policy	Baker (2007);	Baudry (2000); Bosetti and Drouet (2005); Bohringer and Rutherford (2006);	Bosetti et al (2011); Baker and Solak (2013); Held et al (2009); Labriet, Kanudia & Loulou (2012);

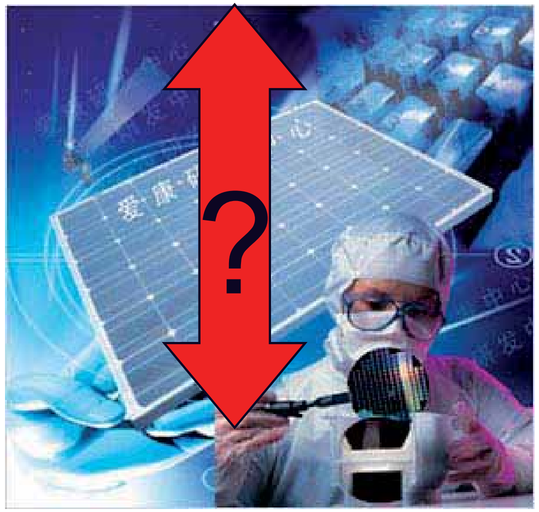
How does Uncertainty and Learning impact optimal climate change policy?



Increasing risk in climate damages or technology



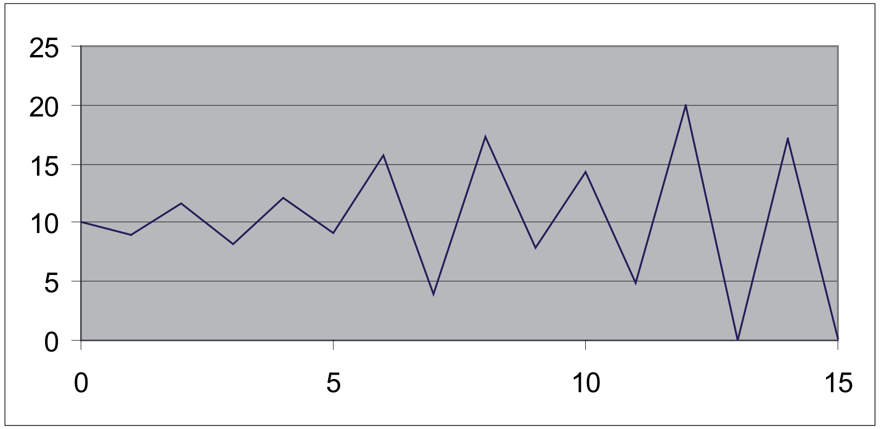
An increase in the amount we expect to learn



Optimal R&D may increase or decrease with an increase in uncertainty about climate damages.

It may increase or decrease with an increase in uncertainty about the outcomes of R&D

Uncertainty and Learning has ambiguous impacts on optimal climate change policy



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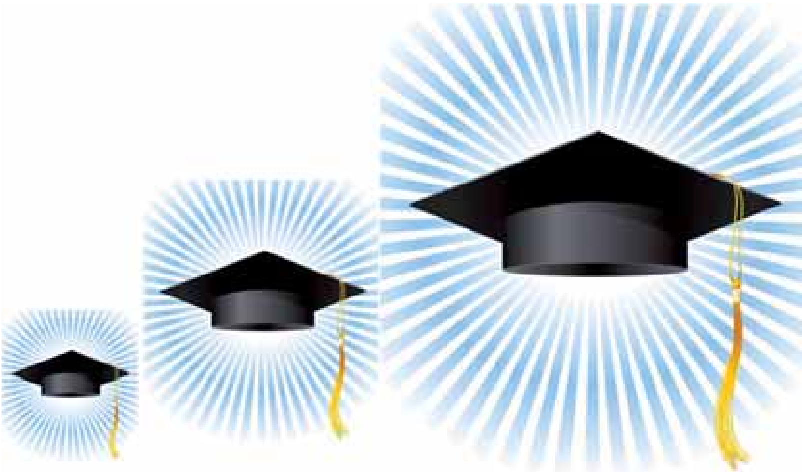

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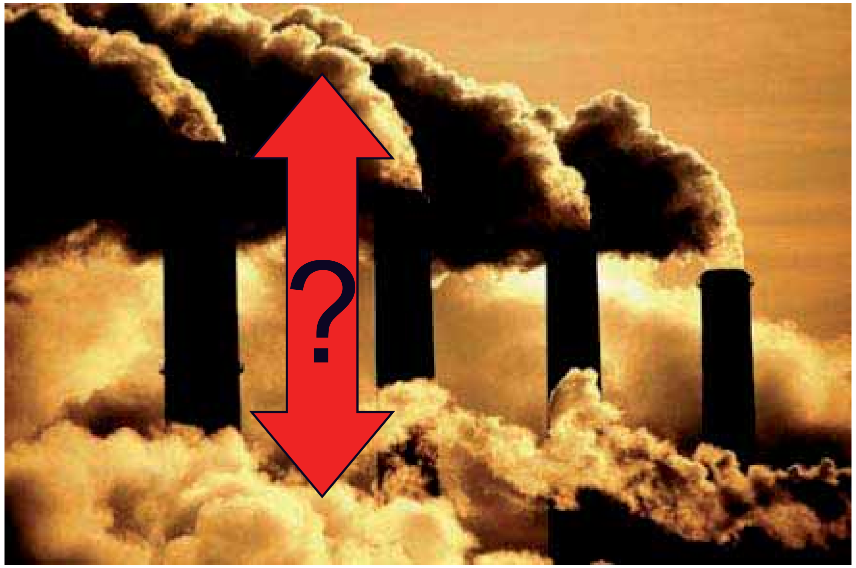
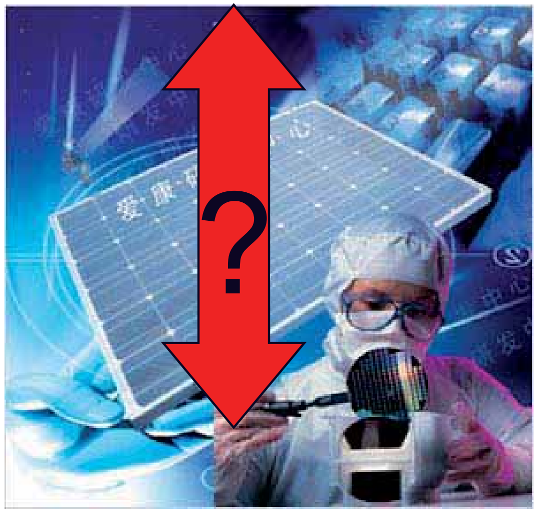


Optimal emissions can increase or decrease



Optimal R&D can increase or decrease

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Slide 41 Table:

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20 Questions

- For each of the questions, please give your estimate of the 1st, 25th, 50th, 75th, and 99th percentile. For example, consider the question “How far is it, in miles, from the center of Amherst to the center of San Francisco, CA. Consider the following answers:

1st	25th	50th	75th	99th
2000	2500	3000	3300	3600

- The responses mean that the probability that the distance is less than 2000 miles is 1%; the probability that the distance is less than 2500 miles is 25%; and the probability that the distance is more than 3600 miles is 1%.