How Should Climate Change Uncertainty

Impact Social Valuation and Policy?

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Booth Finance Lunch Workshop
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What is the challenge?

- human impact on the environment is NOT internalized by markets - social cost $\neq$ private costs
- two sources of uncertainty
  - geosciences: CO_2 emissions today impact the future climate
  - economics: climate change in the future alters economic opportunities and social well-being

What we are aiming for

A computationally tractable laboratory to explore subjective uncertainty including potential model misspecification and ambiguity across models. Goals:

- ▷ assess the impact of uncertainty on climate policy outcomes
- ▷ isolate the forms of uncertainty that are most consequential for these outcomes.

Quantitative story-telling with multiple stories

What does asset valuation provide?

Asset pricing theory: *how do markets assess the investment opportunities in the face of uncertain future net payoffs?*

- ▷ "assets" include financial, physical, human, organizational and environmental "capital"
- ▷ associated with each asset is a prospective sequence of net payoffs to investments

Apply these tools to social instead of market valuation!!

Social cost of carbon (SCC)

Commonly referred to in policy discussions but meanings and targets of measurement *differ* across applications.

We use a well-posed version as an analytical tool to assess the impact of uncertainty.

- externality - carbon emissions alter the climate, which in turn impacts economic opportunities and social well-being in the future
- social cost of carbon includes the socially efficient (Pigouvian) tax on carbon emissions that "corrects" this "externality"

Confronting policy uncertainty

Tension:

- ▷ limited understanding of the mechanism by which policy influences economic outcomes
- ▷ demand for precise answers by the public and/or government policy-makers

Where does uncertainty emerge?

Quantitative storytelling with multiple stories

- ▷ risk: (uncertainty within models) each model has explicit random impulses
- ▷ ambiguity: (uncertainty across models) multiple models give rise to multiple "stories" with different implications
- ▷ misspecification: (uncertainty about models) each model is an abstraction and not intended to be a complete description of reality

Today I will feature ambiguity, but misspecification is also worthy of serious consideration.

Navigating uncertainty

Probability models we use in practice are misspecified, and there is ambiguity as to which among multiple models is the best one.

- aims:
  - use models in sensible ways rather than discard them
  - use tools from probability and statistics to limit the type and amount of uncertainty that is entertained
- aversion - dislike of uncertainty about probabilities over future events
- implementation - target the uncertainty components with the most adverse consequences for the decision maker

Decision theory

Hansen-Miao (2018) propose a recursive implementation of the smooth ambiguity model in continuous time. Discrete-time version originally axiomatized by Klibanoff-Marinacci-Mukerji (2005).

- ▷ ambiguity about local mean specification in the state dynamics
- ▷ axiomatic defense justifies a differential aversion to ambiguity over models
- ▷ equivalence between the smooth ambiguity and recursive robust choice of priors (Hansen-Sargent, 2007)
- ▷ additional adjustment for potential model misspecification as in Hansen and Sargent (2009)

Collapse high-dimensional uncertainty down to a low-dimensional (one or two parameter) representation

Formal approach

- two-player zero-sum differential game
  - stochastic differential equations for state evolution
  - one player is a "fictitious planner" engaged in maximizing social well-being
  - another player investigates the adverse consequences of uncertainty about probabilistic inputs through minimization
- use "relative entropy" to limit or bound the probabilistic uncertainty
- use numerical PDE methods along with some extra twists for computations

Uncertainty in valuation

- construct a “worst-case” probability from the outcome of the two-player game
- use this probability to make uncertainty adjustments for ambiguity and misspecification concerns in valuation formulations including for the SCC

Constructing the adjusted measure

- State evolution:

$$dX_t = \mu_x(X_t, A_t)dt + \sigma_x(X_t, A_t)dW_t$$

  where A is the decision process

- Girsanov transformation

$$dW_t = H_t dt + dW_t^H$$

  with dW_t^H a Brownian increment under the change of measure

Constructing the adjusted measure

- For misspecification include a penalty and minimize

$$\min_{H_t} \frac{\partial V(X_t)}{\partial x} \cdot [\sigma_x(X_t, A_t) H_t] + \frac{\xi_m}{2} H_t \cdot H_t$$

- Let θ be an unknown parameter. Hansen-Miao implementation of smooth ambiguity

$$-\xi_a \log \left(\int_\Theta \exp \left[-\frac{1}{\xi_a} \frac{\partial V(X_t)}{\partial x} \cdot \mu_x(X_t, A_t; \theta) \right] dQ_t(\theta) \right)$$

where the expectation is taken over θ.

Smooth ambiguity and robust priors

- Recall

$$-\xi_a \log\left(\int_\Theta \exp\left[-\frac{1}{\xi_a}\frac{\partial V(X_t)}{\partial x}\cdot \mu_x(X_t, A_t;\theta)\right] dQ_t(\theta)\right)$$

- Solve

$$\min_{g,\int g dQ_t=1} \int \left[\frac{\partial V(X_t)}{\partial x}\cdot \mu_x(X_t, A_t;\theta) + \xi_a \log g(\theta)\right] g(\theta) dQ_t(\theta)$$

- Smooth ambiguity equivalent to a change in the probabilities over θ with a relative entropy penalty. Implied worst-case relative density:

$$\propto \exp\left[-\frac{1}{\xi_a}\frac{\partial V(X_t)}{\partial x}\cdot \mu_x(X_t, A_t^*;\theta)\right]$$

where A^* is the maximizing decision process.

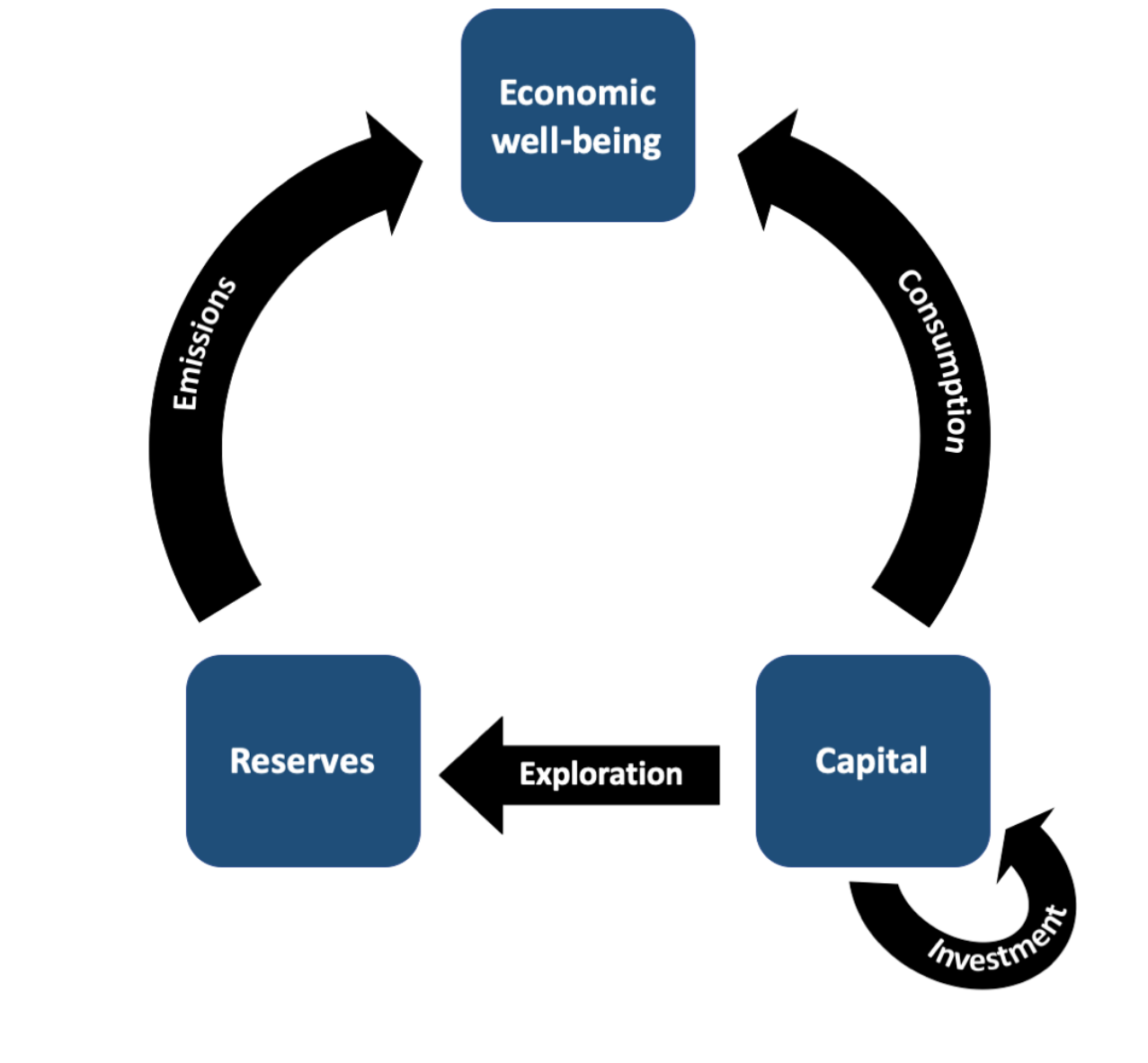
SCC as an asset price

Social cash flow

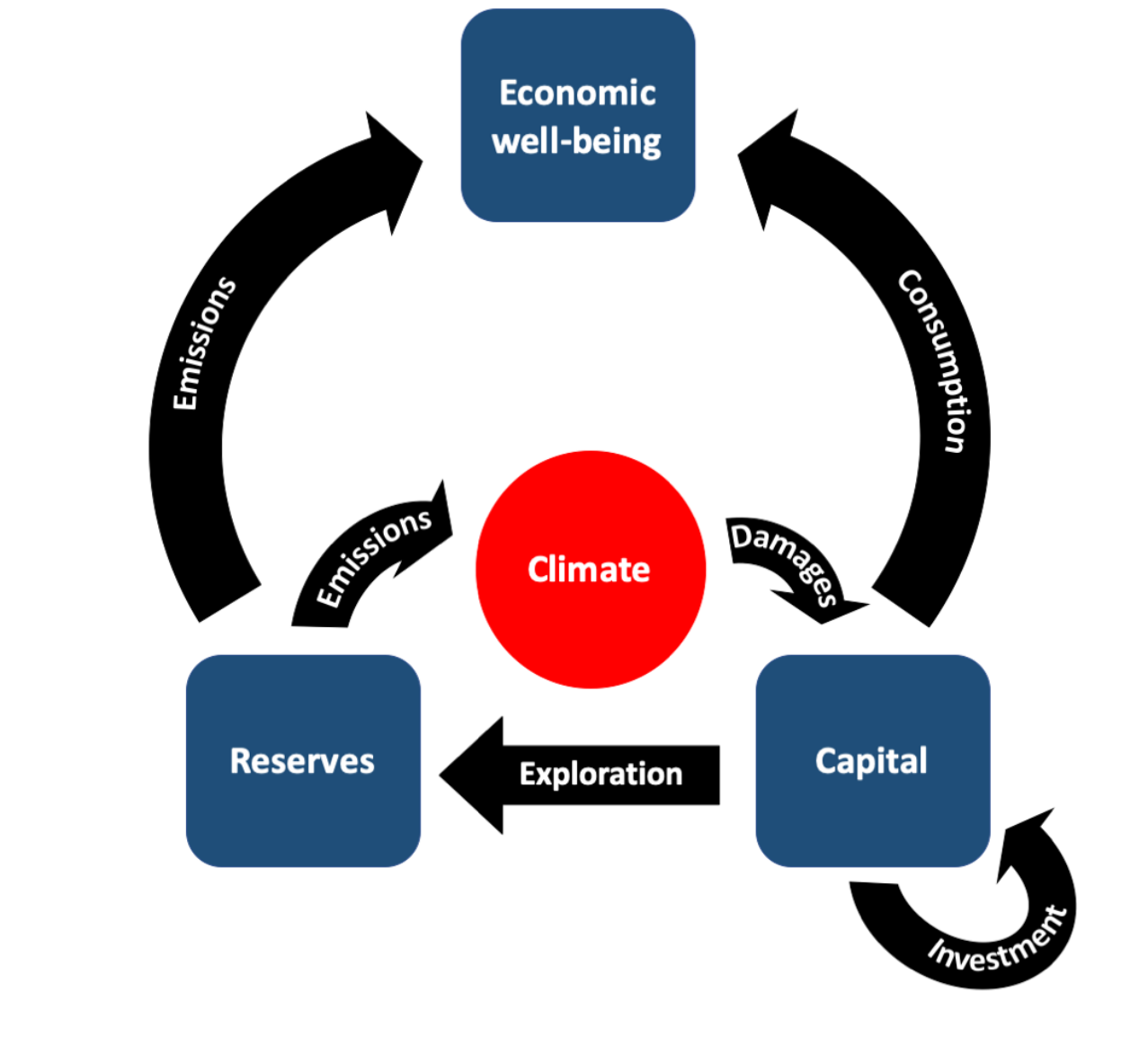
- Form nonlinear impulse responses of emissions today on damages in the future
- Incorporate marginal utility adjustments
- Depict the interacting uncertainty about economic damages and climate change
- Use stochastic discounting under the uncertainty-adjusted probabilities to accommodate concerns for ambiguity and model misspecification

Social cost of carbon agglomerates the social cash flows using stochastic discounting and adjusting for uncertainty

Modeling Framework



Modeling Framework



Environment: information

- $W \doteq \{W_t : t \geq 0\}$ is a multivariate standard Brownian motion
- Let $Z \doteq \{Z_t : t \geq 0\}$ be a stochastically stable, multivariate forcing process with evolution:

$$dZ_t = \mu_z(Z_t)dt + \sigma_z(Z_t)dW_t.$$

Will abstract from Z in today's talk.

Environment: production

AK model with adjustment costs

- Evolution of capital K

$$dK_t = K_t \left[\mu_k(Z_t)dt + \phi_0 \log\left(1 + \phi_1 \frac{I_t}{K_t}\right) dt + \sigma_k \cdot dW_t \right].$$

  where I_t is investment and $0 < \phi_0 < 1$ and $\phi_1 > 1$.

- Production

$$C_t + I_t + J_t = \alpha K_t$$

  where C_t is consumption and J_t is investment in the discovery of new fossil fuel reserves.

Environment: reserves

- Reserve stock, R, evolves according to:

$$dR_t = -E_t dt + \psi_0 (R_t)^{1-\psi_1} (J_t)^{\psi_1} + R_t \sigma_R \cdot dW_t$$

  where $\psi_0 > 0$ and $0 < \psi_1 \leq 1$ and E_t is the emission of carbon.
- Hotelling fixed stock of reserves is a special case with $\psi_0 = 0$

Economic impacts of climate change

i) adverse impact on societal preferences

ii) adverse impact on production possibilities

iii) adverse impact on the growth potential

Simplified climate dynamics

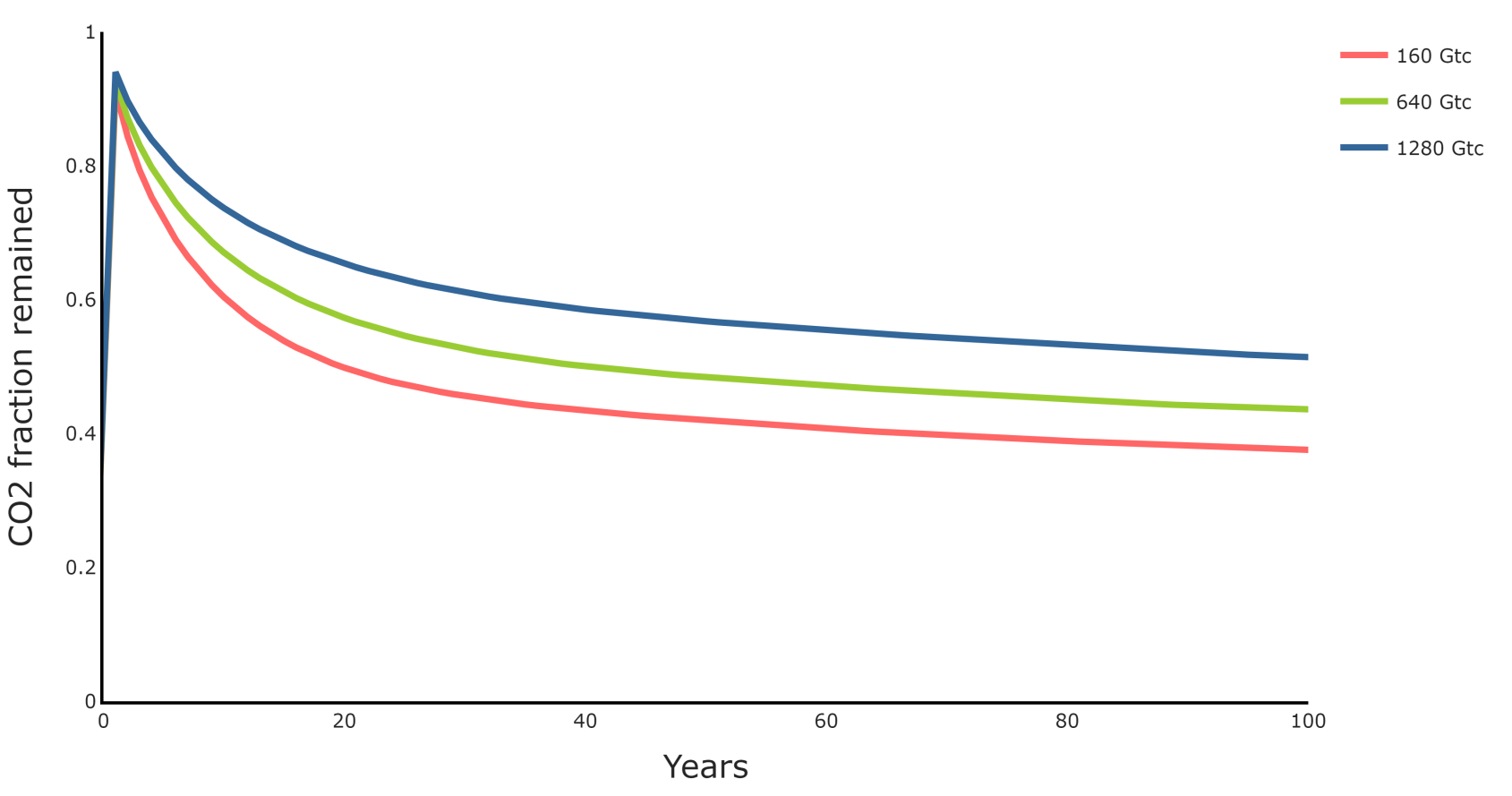
Two sources:

i) emissions induce changes in the future carbon concentration in the atmosphere

ii) changes in carbon concentration alter temperature in the future

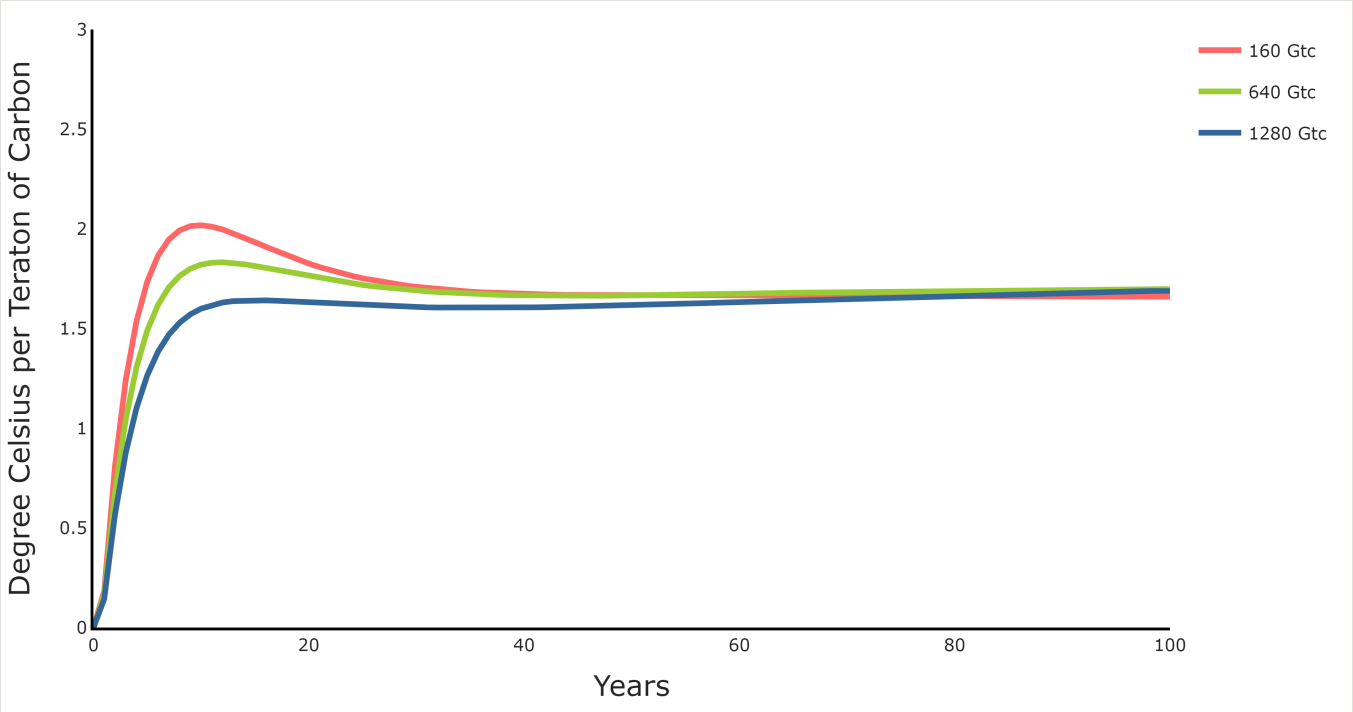
We characterize the convolution of these two ingredients using results of "pulse experiments" for alternative climate models.

Carbon responses to emission pulses



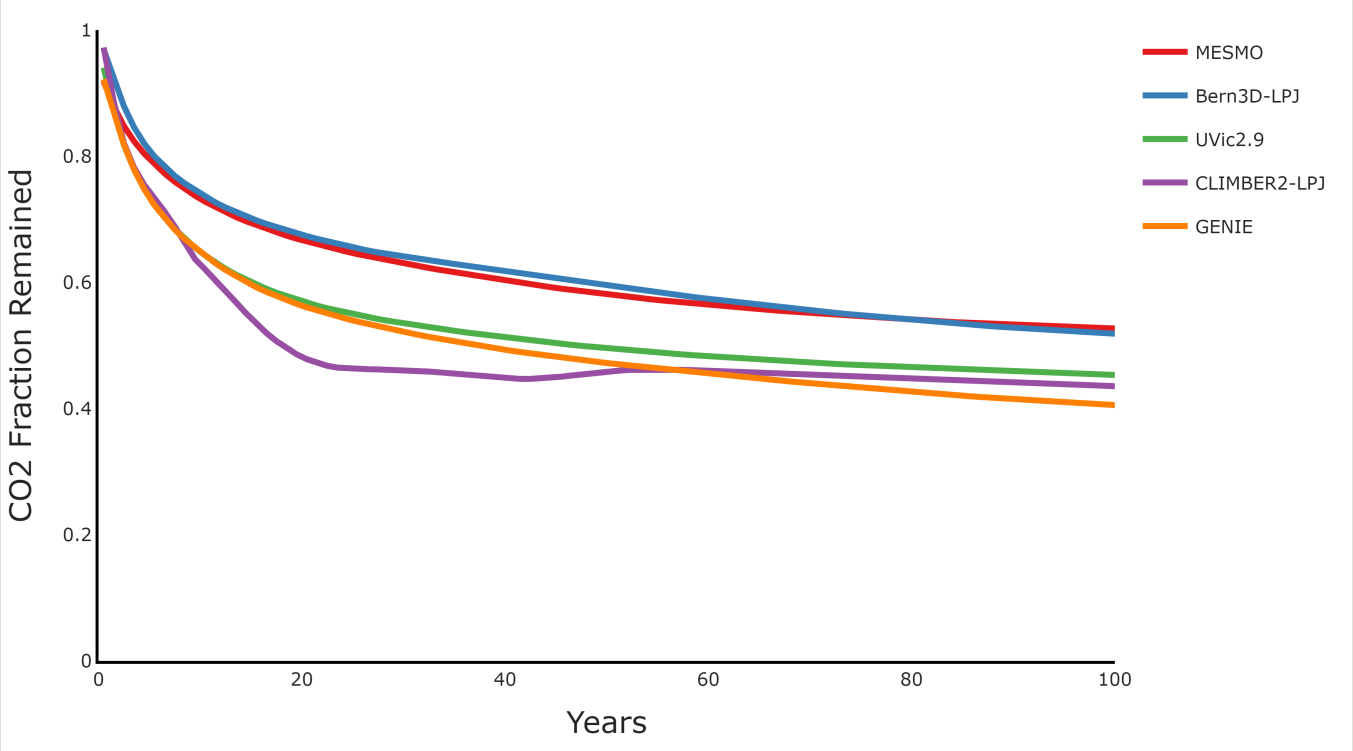
UVIC model of carbon dynamics

Temp responses to emission pulses



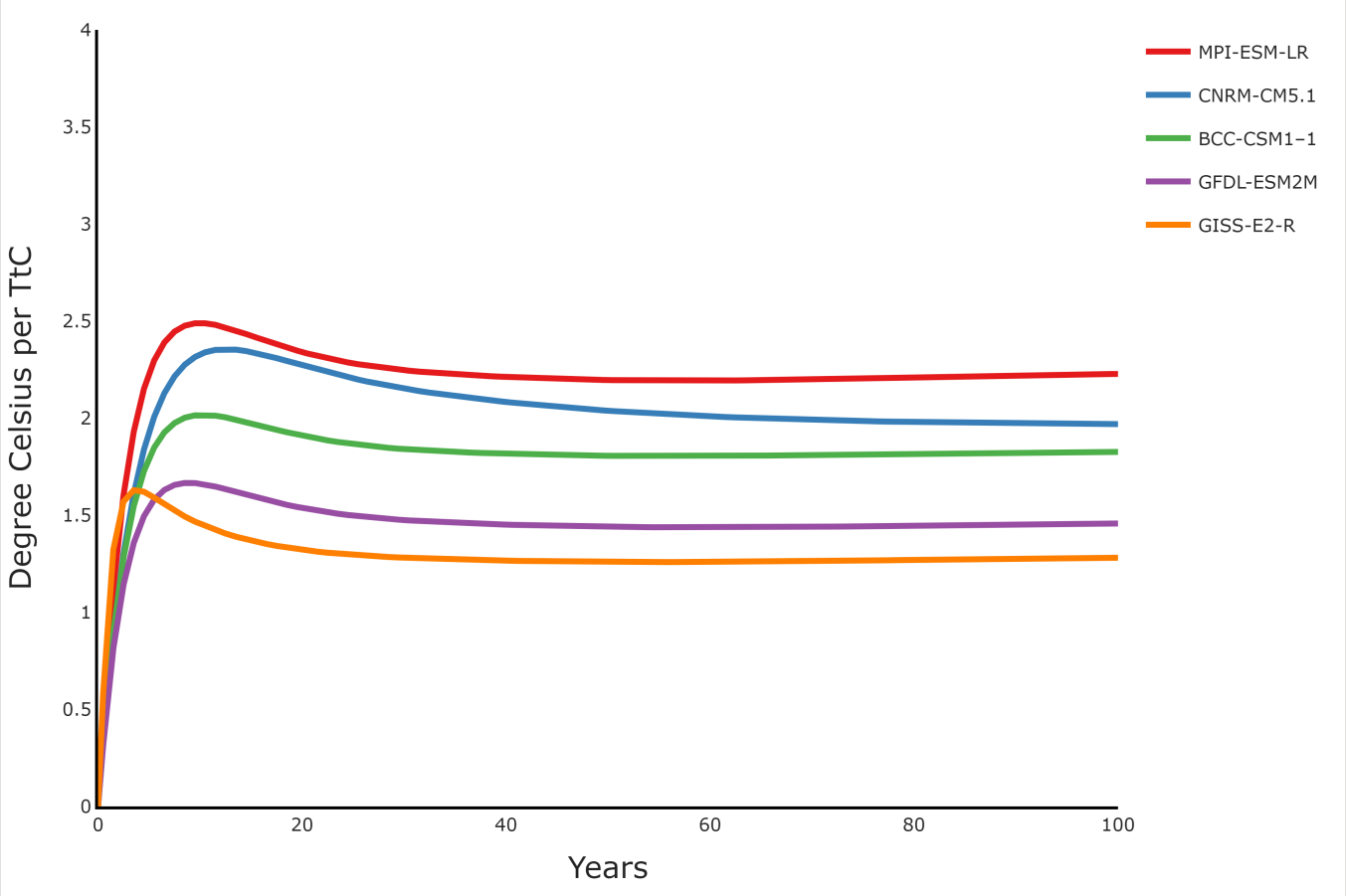
UVIC model carbon dynamics coupled with the BBC model of temperature dynamics approximated as in Geoffroy (2013)

Model ambiguity for carbon dynamics



100 gigaton pulse responses for five models

Model ambiguity for temperature dynamics



100 gigaton pulse responses for five models

Simplified climate dynamics

Today, and in previous work we use an approximation that simplifies model comparisons

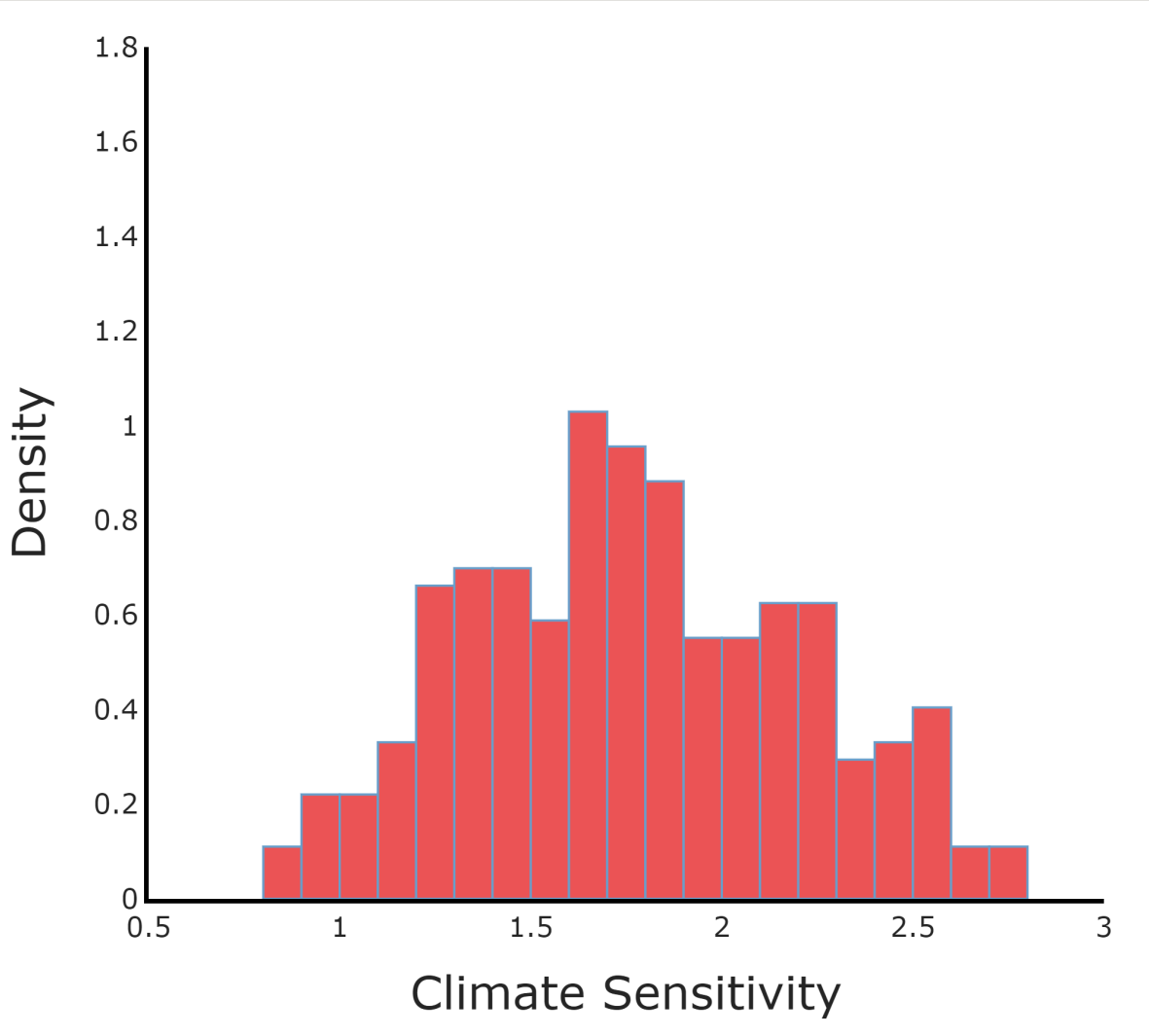
- ▷ Matthews *et al* (2009) and others have purposefully constructed an approximation to or a summary of climate models outputs:

$$\text{temperature change} \approx CCR \times \text{ cumulative emissions}$$

- ▷ abstract from transient changes in temperature

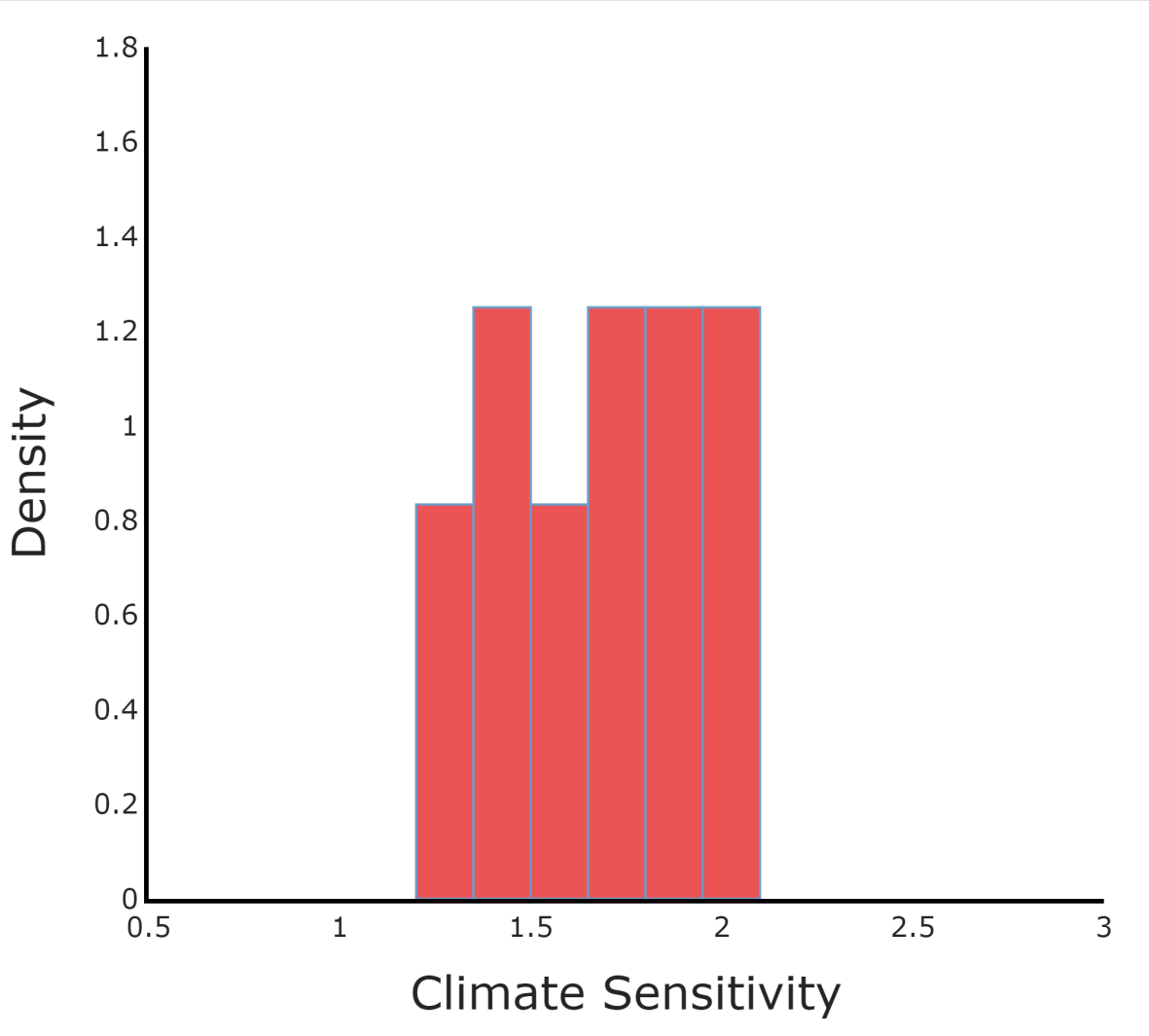
Emissions today have a long-lasting impact on temperature in the future where CCR (cumulative carbon response) is a climate sensitivity measure.

Model ambiguity: combined



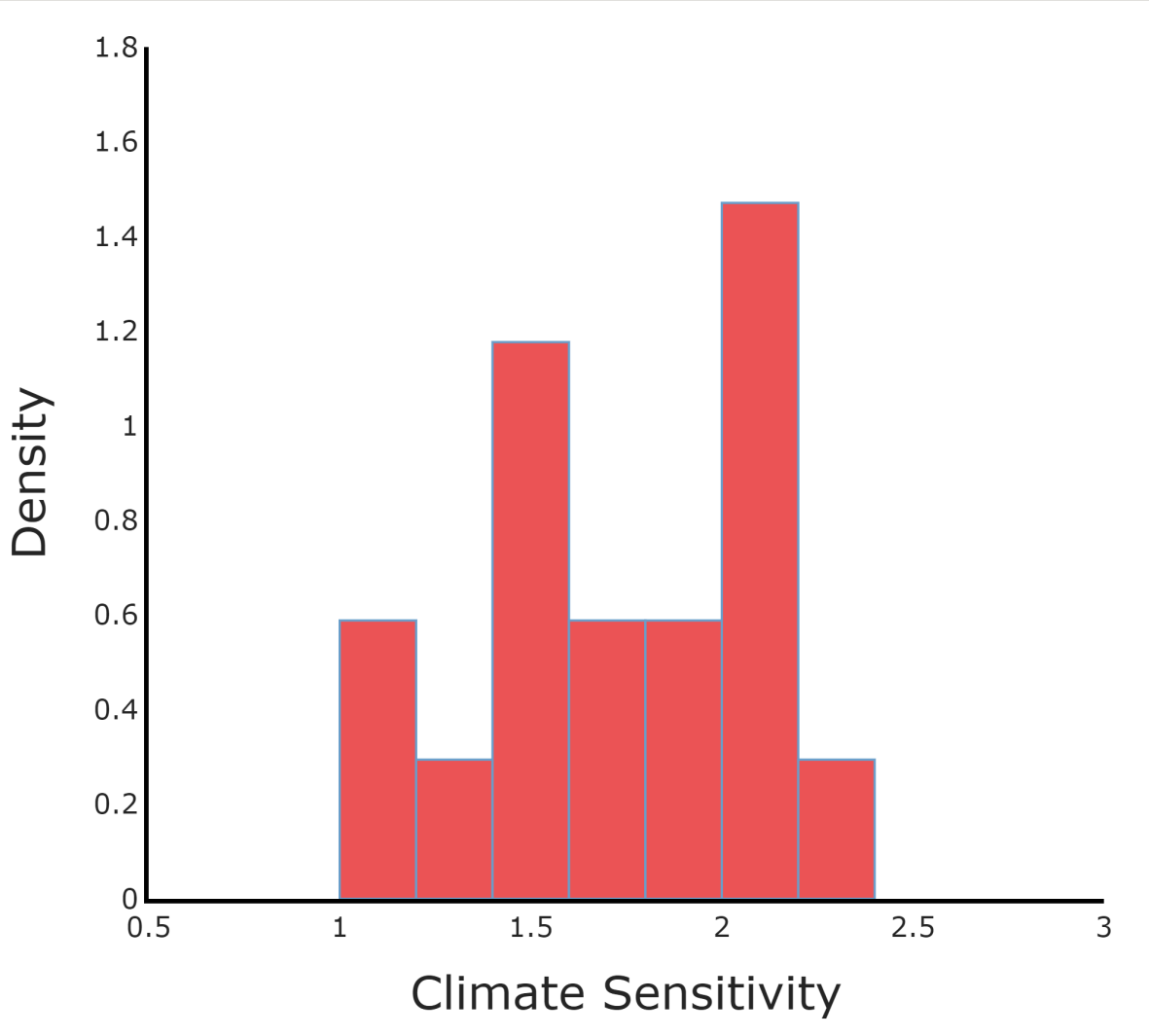
16 carbon dynamic models and 17 temperature dynamic models

Model ambiguity: carbon



16 carbon dynamic models

Model ambiguity: temperature



17 temperature dynamic models

Damage specification

Posit a damage process, N, to capture negative externalities on society imposed by carbon emissions.

$$\log N_t = \Lambda(T_t - T_{pre}) + \nu_n(Z_t)$$

where in our illustration, for $\tau \leq \overline{\lambda}$:

$$\Lambda(\tau) = \lambda_1 \tau + \frac{\lambda_2}{2}\tau^2$$

with an additional penalty for $\tau > \overline{\lambda}$:

$$\frac{\lambda_2^+}{2}\left(\tau - \overline{\lambda}\right)^2.$$

- ▷ λ_2 gives a nonlinear damage adjustment
- ▷ $\lambda_2^+ > 0$ gives a smooth alternative to a carbon budget

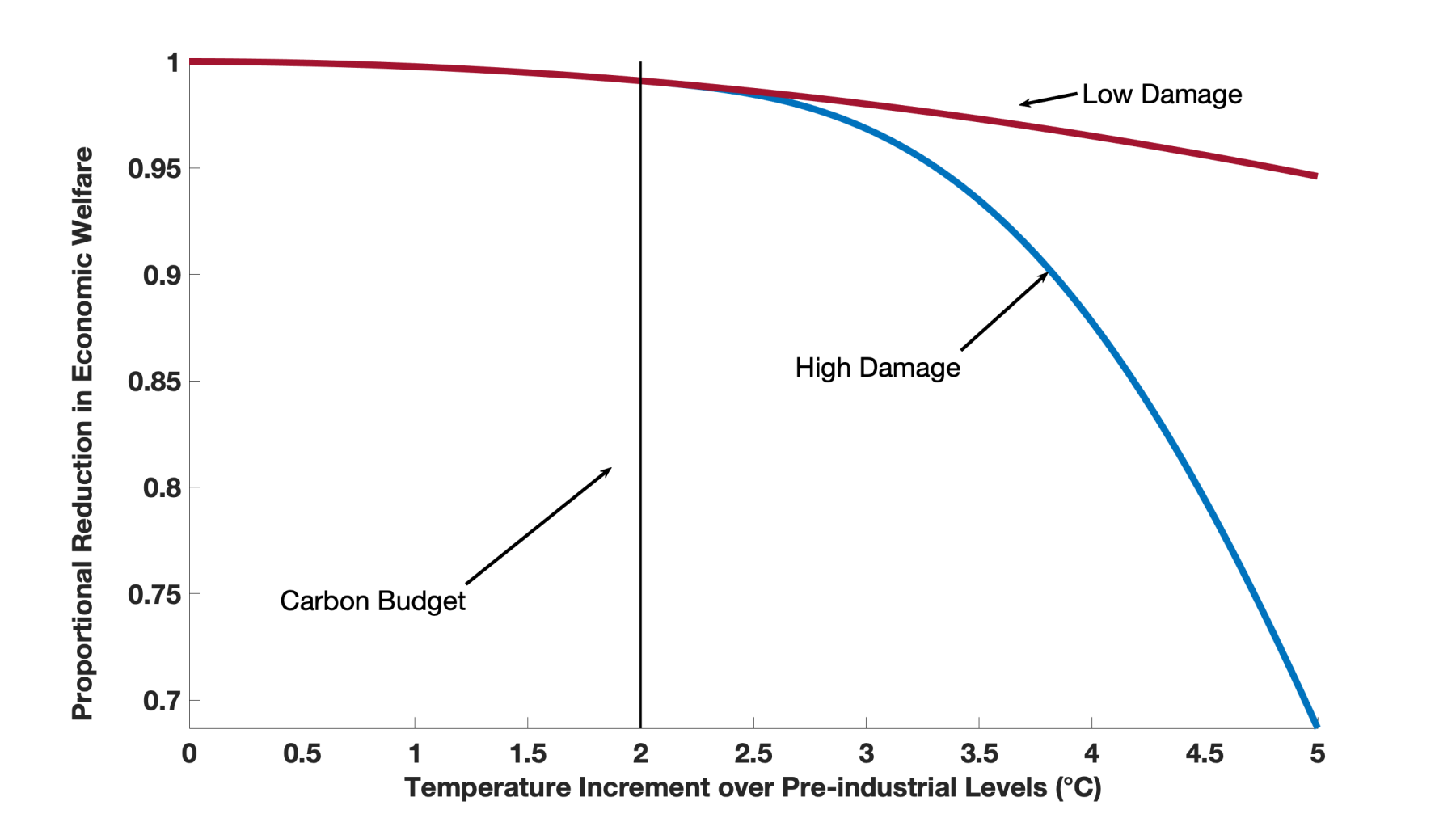
Proportional damages

- the per period (instantaneous) contribution to preferences is:

$$\delta(1-\eta)\left(\log C_t - \log N_t\right) + \delta\eta \log E_t$$

  where $\delta > 0$ is the subjective rate of discount and $0 < \eta < 1$ is a preference parameter that determines the relative importance of emissions in the instantaneous utility function.
- equivalently this is a model with proportional damages to consumption and or production.

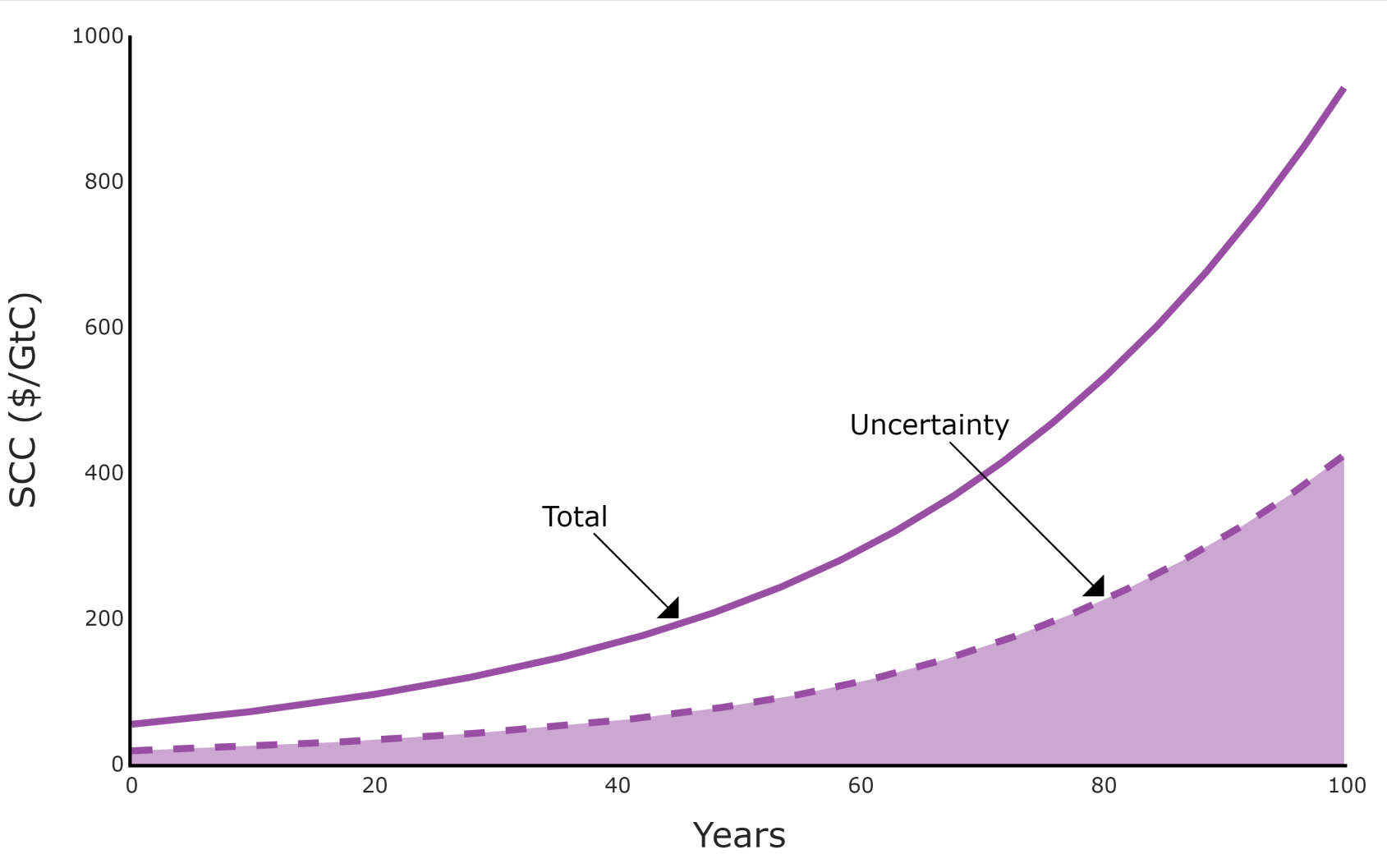
Proportional damage uncertainty



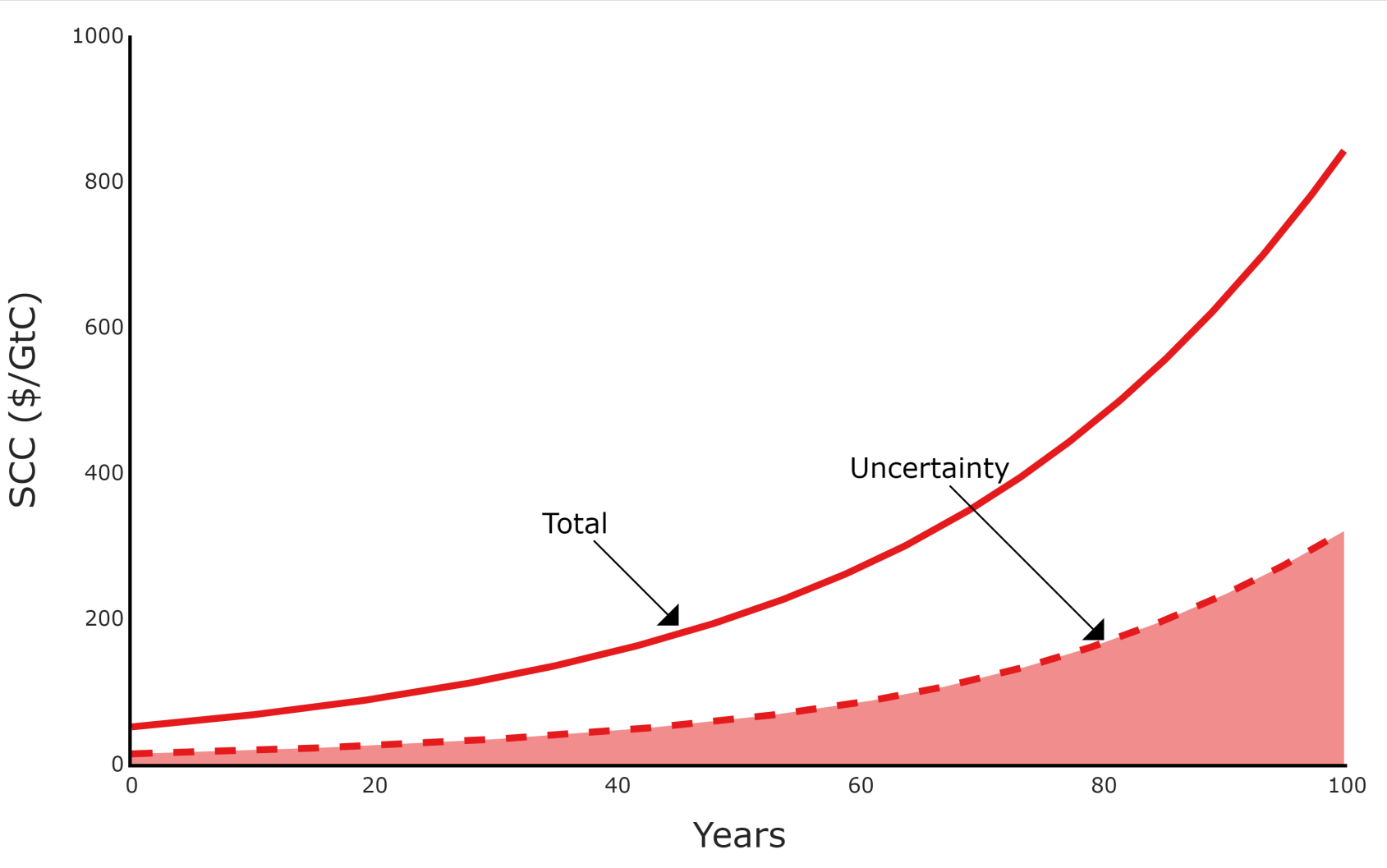
Uncertainty decomposition

- Compute the difference between two discounted expected values with different probabilities
  - one forms probabilities by forming simple averages over those implied by alternative models
  - another forms ambiguity-adjusted probabilities deduced from the planner's problem
- Quantify the impact of uncertainty on the SCC (social cost of carbon).

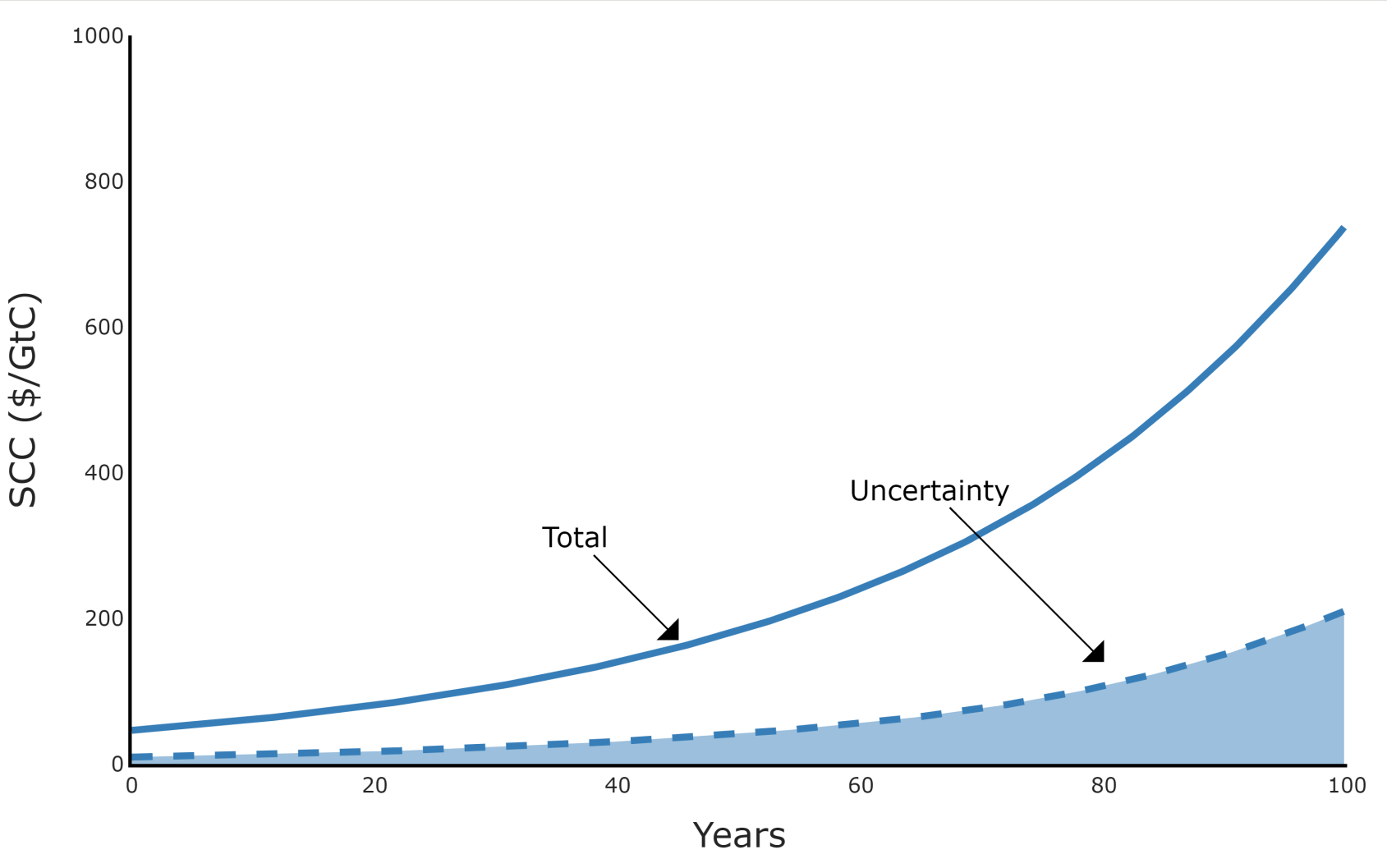
SCC: combined model ambiguity



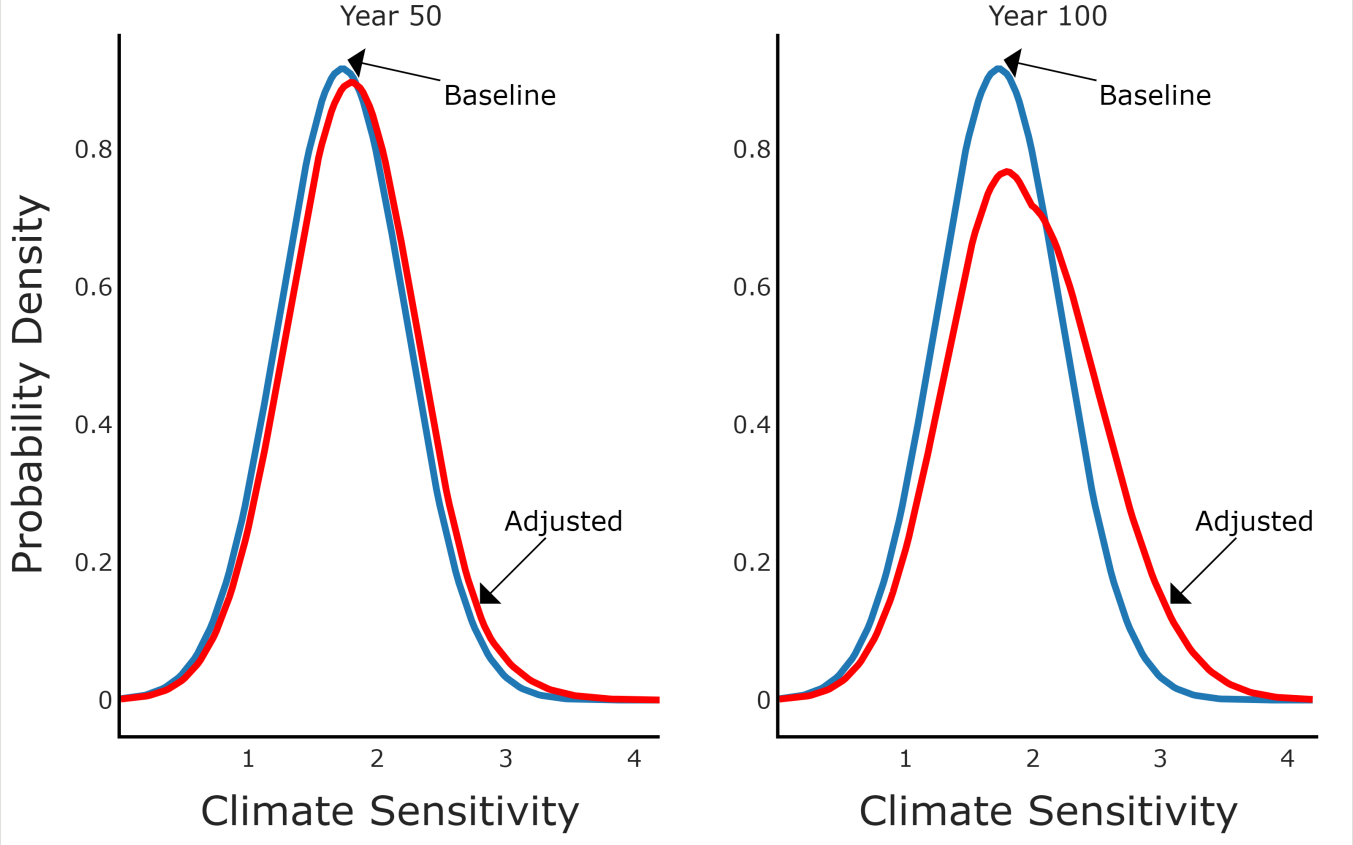
SCC: temperature model ambiguity



SCC: carbon model ambiguity



Ambiguity-adjusted probabilities



The initial weighting is the same for both the low- and high-damage specifications. The ambiguity-adjusted probabilities remain very close to this at year 50, but are tilted towards the high damage specification (probability .58) at year 100.

Nonlinearity and uncertainty

Observations:

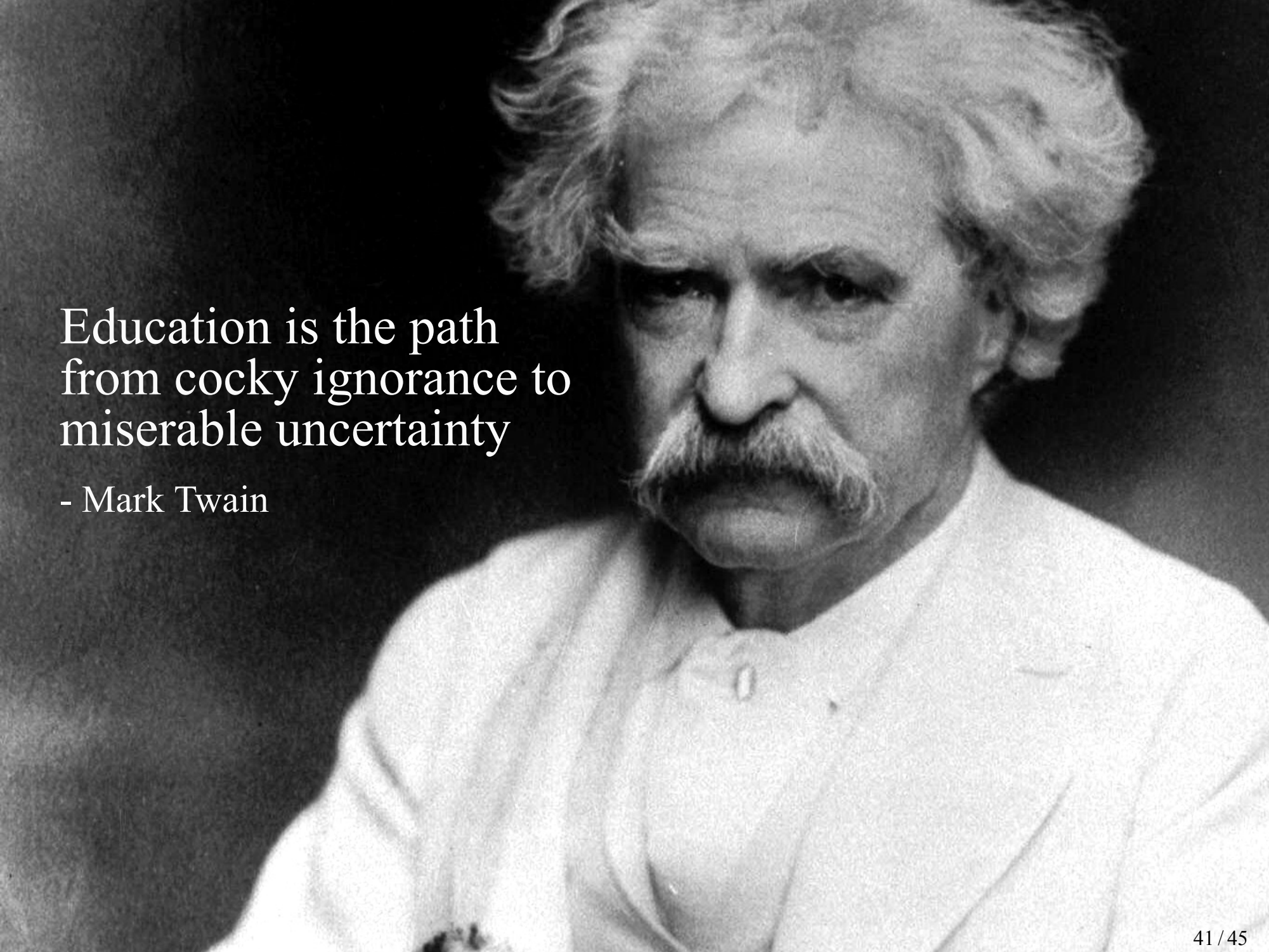
- proportionality breaks down with large pulses
- additional sources of nonlinearity
  - permafrost
  - nonlinear temperature feedback, Zalliapin and Ghil (2010)

Richer economic model

- energy transition: accelerating the shift away from fossil fuels and towards renewable energy
- nature-based solutions: increasing sink capacity and enhancing resilience through biodiversity conservation
- resilience and adaptation: endogenous economic responses to climate change

These extensions will:

- open additional channels with uncertain consequences
- allow us to investigate how alternative policies close the gap between actual prices and idealized notions of the social cost of carbon


Education is the path
from cocky ignorance to
miserable uncertainty
- Mark Twain

Model we used

Carbon cycle models:

- Bern3D-LPJ，University of Bern 3D Earth system model with Lund–Potsdam–Jena dynamic global vegetation (Bern3D-LPJ; Ritz et al. 2011; Stocker et al. 2011)
- CLIMBER2-LPJ，the Potsdam Institute Climate and Biosphere Model (Petoukhov et al. 2000; Montoya et al. 2005)
- GENIE, the Grid Enabled Integrated Earth system model (GENIE) adapted with an implementation of land use change (Holden et al. 2013)
- MESMO, version 1.0 of the Minnesota Earth System Model for Ocean biogeochemistry (MESMO 1.0; Matsumoto et al. 2008) (University of Minnesota)
- UVic.29, version 2.9 of the University of Victoria Earth System Climate Model (UVic ESCM 2.9; Weaver et al. 2001; Eby et al. 2009)

Model we used

Temperature models:

- BCC-CSM1-1, Beijing Climate Center, China Meteorological, Administration Instituto Nacional de Pesquisas Espaciais (National Institute for Space Research)
- GFDL-ESM2M, NOAA Geophysical Fluid Dynamics Laboratory
- CNRM-CM5.1, Centre National de Recherches Météorologiques / Centre Européen de Recherche et Formation, Avancée en Calcul Scientifique
- GISS-E2-R, NASA Goddard Institute for Space Studies
- MPI-ESM-LR. Max Planck Institute for Meteorology

Complementary econ references

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