Impact of Geoscientific and Economic Uncertainty on Social Valuation

Lars Peter Hansen (University of Chicago)
Virtual Finance Seminar
Collaborators: Barnett (ASU), Brock (Wisconsin),
Chavez (Imperial) and Ghil (ENS and UCLA)
May 29, 2020

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"

SCC is an asset price

- social cash flows of interest are nonlinear impulse response functions with two interconnected contributions
  - geoscience explores how changes in CO_2 emissions alter temperature in the future
  - economics investigates how changes in temperature alter economic opportunities in the future
- social cost of carbon agglomerates the social cash flows using stochastic discounting and adjusting for uncertainty

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

Haunted by Hayek's forewarning

"Even if true scientists should recognize the limits of studying human behaviour, as long as the public has expectations, there will be people who *pretend* or *believe* that they can do more to meet popular demand than what is really in their power."
(From Hayek's Nobel address, 1974)

For quantitative policy analysis, how should we acknowledge the limits to our understanding.

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

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)

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

Adjusting for 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 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

$$\frac{\xi_m}{2} H_t \cdot H_t$$

  and minimize.

- Hansen-Miao implementation of smooth ambiguity

$$-\xi_a \log E \left(\exp \left[-\frac{1}{\xi_a} \mu_x(X_t, A_t; \theta) | X_t \right] \right)$$

  where the expectation is taken over θ. Equivalent to a change in the probabilities over θ with a relative entropy penalty

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

Observation: shadow prices are computed using an efficient allocation and not necessarily what is observed in competitive markets

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

Climate literature suggests an approximation that simplifies model comparisons

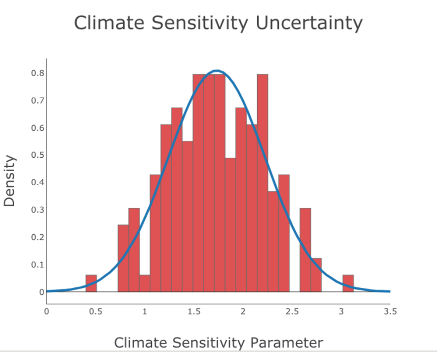
- Matthews *et al* (2009) and others have purposefully constructed an approximation to or a summary of climate models outputs:

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

- 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.

Climate sensitivity and uncertainty



Histogram and density for the climate sensitivity parameter across models. Evidence is from MacDougall-Swart-Knutti (2017).

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

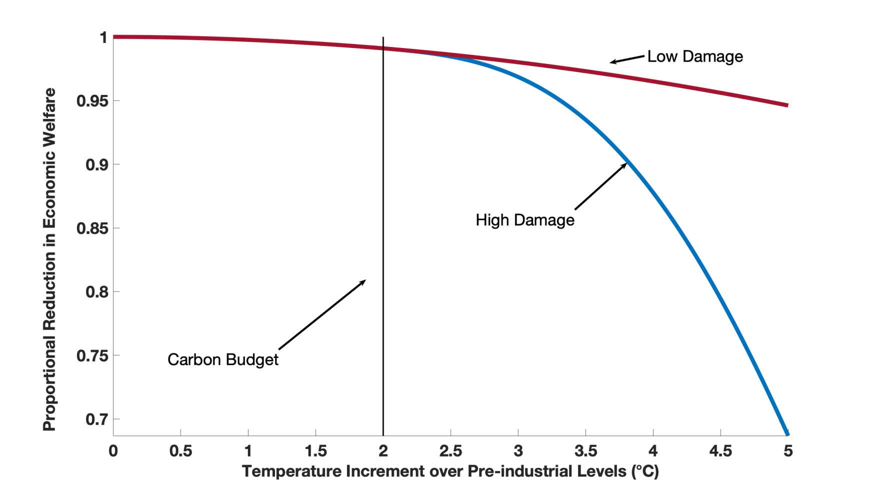
- the per period (instantaneous) contribution to preferences is:

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

  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.

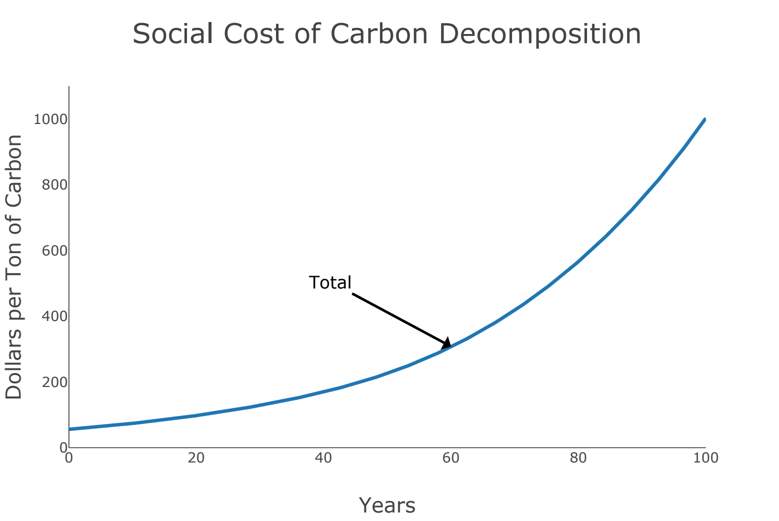
- equivalently this is a model with proportional damages to consumption and or production.

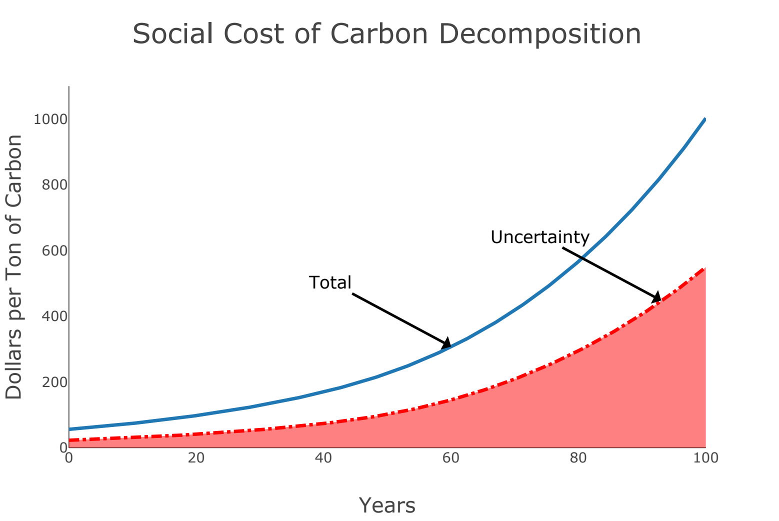
Proportional damage uncertainty



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).


Social Cost of Carbon Decomposition
Dollars per Ton of Carbon
1000
800
600
400
200
0
Total
0
20
40
60
80
100
Years


Social Cost of Carbon Decomposition
Dollars per Ton of Carbon
Years
Total
Uncertainty
0
200
400
600
800
1000
0
20
40
60
80
100

Temperature dynamics, revisited

Consider the dynamic evolution:

$$dF_t = dF_t^1 + dF_t^2 - \gamma dT_t,$$
$$c dT_t = \left(Rad_t^i - Rad_t^o\right) dt + 5.35 \left(\log F_t - \log F_{pre}\right) dt + \sigma_\tau \cdot dW_t.$$

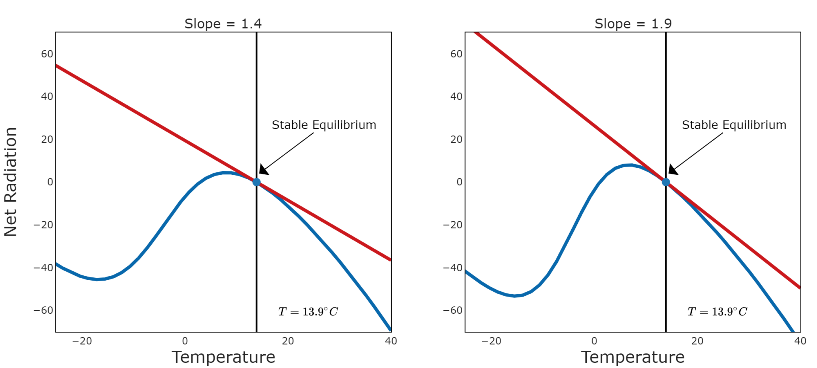
where

- F_t is the carbon in the atmosphere and F_{pre} is the pre-industrial value of F_t
- $dF_t^1 = (1-\beta)E_t$ and $dF_t^2 = -\zeta F_t^2 + \beta E_t$.
- Rad_t^i is incoming radiation and Rad_t^o is outgoing radiation.

We set γ to zero. We follow Ghil and collaborators [e.g., Ghil and Lucarini, 2020] and use their nonlinear specification of net radiation:

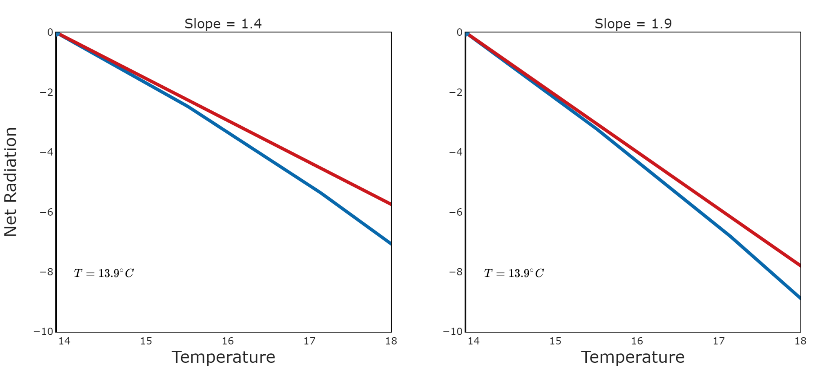
$$Rad_t^i - Rad_t^o = \rho(T_t)$$

Nonlinear model of net radiation



The blue line represents the Ghil model, and the red line a local linear approximation. Each panel imposes a different slope.

Zoomed in version



The blue line represents the Ghil model, and the red line a local linear approximation. Each panel imposes a different slope.

Alternative impulse responses

Use a local impulse response by studying marginal changes of temperature and damages to changes in emissions.

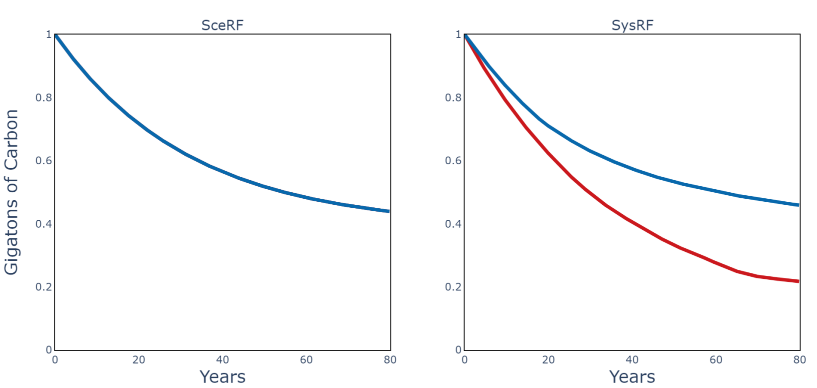
- ▹ climate system combined with an exogenous scenario for emissions - scenario response function (SceRF)
- ▹ full system solution to our planner's problem with endogenous emissions - system response function (SysRF)

Observation: Given nonlinearity, these impulse response functions are state dependent and are affected by the prospective path of the state variables

Emission scenarios

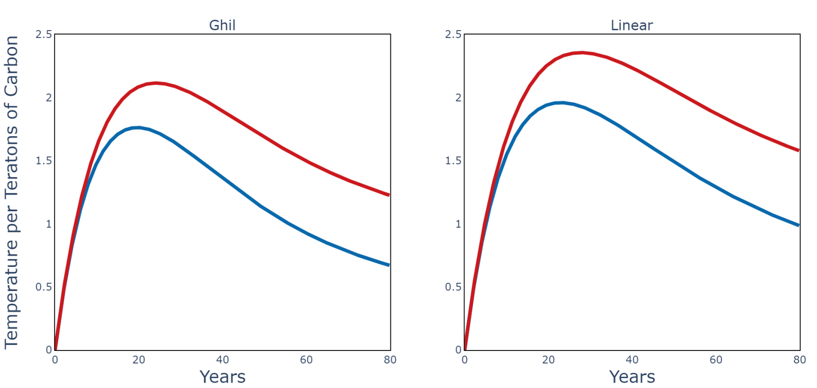
- common in climate science is to use representative concentration pathway (RCP) scenarios: RCP's are exogenous paths for atmospheric carbon over time
- we use two paths for emissions generated by deterministic simulations from the planner's solution to the high damage and low damage specifications
  - high damage specification starts at about 12 gigatons of carbon
  - low damage specification starts at about 28 gigatons of carbon

Atmospheric carbon responses



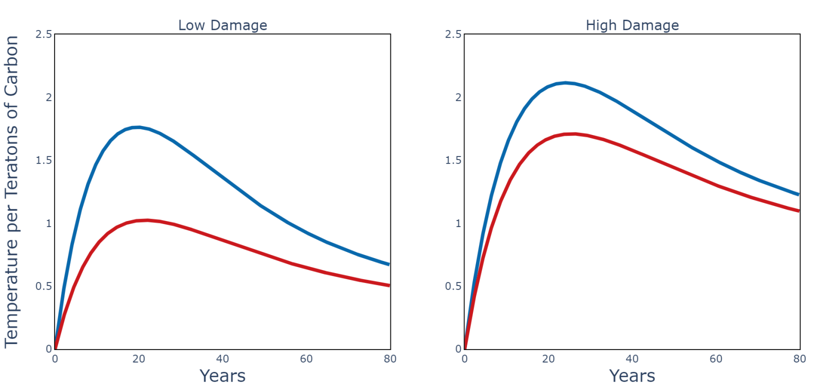
The blue line represents the impulses for Ghil model using low damage specification, and the red line represents high damage specification.

Temperature impulse responses



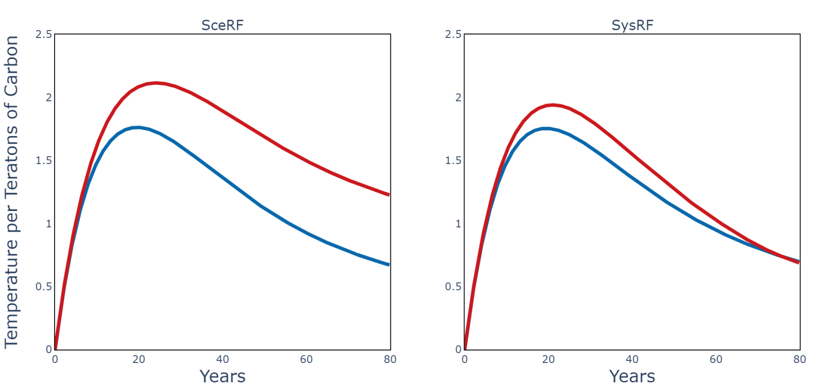
The left panel are the SceRFs for the nonlinear Ghil model and the right panel from the linear approximation. Blue line presumes the low damage scenario, and the red line presumes the high damage scenario.

Temperature responses for different impulse dates



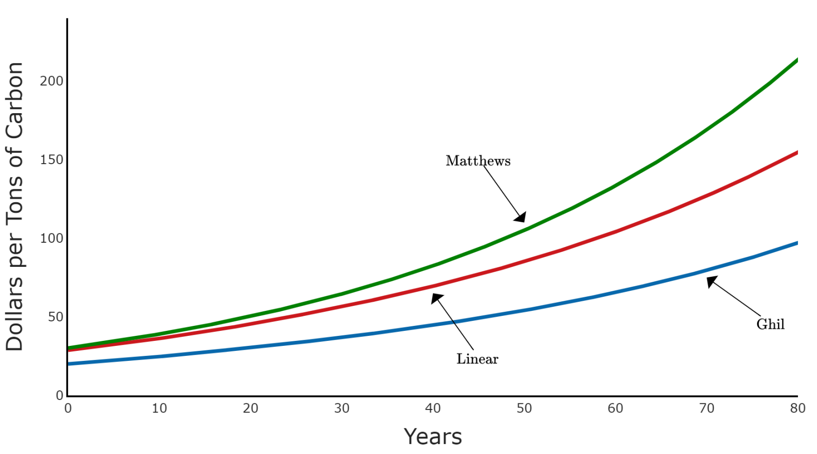
Blue solid line alters emissions at year 0, and the red dashed line alters emissions at year 40.

Temperature SceRF versus SysRF



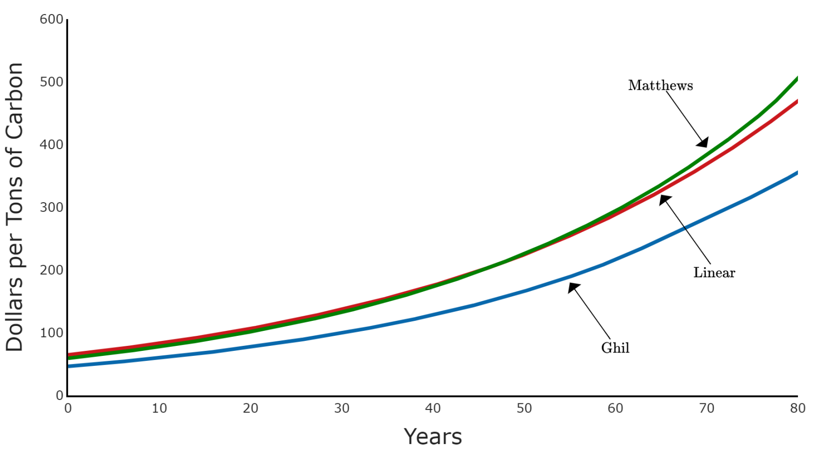
The blue line represents the impulses for Ghil model using low damage function, and the red line represents high damage function.

SCC: low damage



The blue line uses the Ghil model of temperature dynamics; the red line the linear approximation; and the green line the Matthews approximation with $CCR = 1.36$.

SCC: high damage



The blue line uses the Ghil model of temperature dynamics; the red line the linear approximation; and the green line the Matthews approximation with $CCR = 1.73$.

Next steps

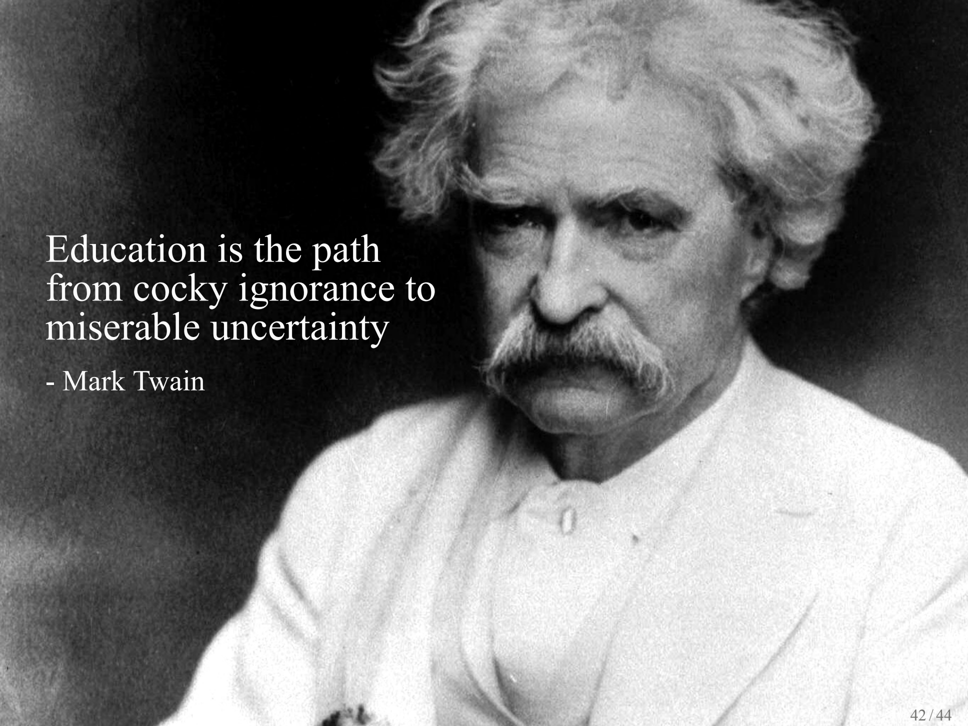
So far, we have illustrated the documented sensitivity about temperature and dynamics and damages "outside the model." Both the private sector and policy makers also confront this as "uncertainty." Next, we will formally incorporate this uncertainty "inside the model" and investigate the consequences.

Future responses to climate change

- 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

Complementary econ references

- Cai, Judd, and Longtzek (2017), *The Social Cost of Carbon with Climate Risk*
- Golosov, Hassler, Krusell, and Tsyvinski (2014) *Optimal Taxes on Fossil Fuel in General Equilibrium*
- Hambel, Kraft, and Schwartz (2018), *Optimal Carbon Abatement in a Stochastic Equilibrium Model with Climate Change*
- Lemoine and Traeger (2016), *Ambiguous Tipping Points*
- Li, Loch-Temzelides (2016), *Robust Dynamic Energy Use and Climate Change*
- Millner, Dietz, and Heal (2013), *Scientific Ambiguity and Climate Policy*
- Nordhaus (2018), *Projections and Uncertainties About Climate Change in an Era of Minimal Climate Policies*
- Weitzman (2012), *GHG Targets as Insurance Against Catastrophic Climate Damages*

Complementary geosci references

- Allen et al. (2009), *Warming Caused by Cumulative Carbon Emissions Towards the Trillionth Tonne*
- Friedlingstein et al. (2019), *Global Carbon Budget 2019*.
- Ghil (2019), *A Century of Nonlinearity in the Geosciences*
- Joos et al. (2013), *Carbon Dioxide and Climate Impulse Response Functions for the Computation of Greenhouse Gas Metrics: A Multi-Model Analysis*
- Lenton and Hutingford (2003), *Global Terrestrial Carbon Storage and Uncertainties in its Temperature Sensitivity Examined with a Simple Model*
- North, Cahalan, and Coakley (1981), *Energy Balance Climate Models*
- Zickfeld et al. (2013), *Long-Term Climate Change Commitment and Reversibility: An EMIC Intercomparison*